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Roulette Wheel Selection Algorithm (RWSA) and Reinforcement Learning (RL) for personalizing and improving e-learning system

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Declaration

I, **Melvin Abes Ballera** hereby declare that this work has not been previously submitted and approved for the award of a degree by this or any other university. To the best of my knowledge and belief, this thesis contains no material previously published or written by another person except where due reference is made in the thesis itself.

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Abstract

Various mechanisms to improve the learning process with the main objective of maximizing learning and dynamically selecting the best teaching operation to achieve learning goals have been done in the field of personalized learning. Despite recommending a personalized learning sequence, e-learning instructional strategists have failed to perform or address the necessary corrective measures to remediate immediately learning misconceptions or difficulties. As e-learning materials continue to evolve, it is necessary that an alternative, dynamic, and real time multi-performance be developed and implemented in e-learning systems. Two major contributions in the field of e-learning have been asserted by this study: it personalizes the learning sequence using reversed roulette wheel selection algorithm blended with linear ranking based on real time, dynamic multi-based performance matrix; and implements the reinforcement and mastery learning to motivate students and improve their learning output.

Based on experiments, personalized learning sequence (PLS) were dynamic and heuristic and simultaneously considers the curriculum difficulty level and the curriculum continuity of successive curriculum while implementing personalized learning process. From 34%, the passing rate of the students is increased by 54% making the overall passing rate to 88%. The increase can be attributed to the reinforcement process and mastery learning where various control mechanism are implemented to guarantee learning process. Digital transcripts based on students' perceptions and experiences positively correlate with the result of document sentiment of +.321 while theme analysis revealed a positive attitude with the extracted words in the documents such as: *very happy*, *friends*, *motivate*, *improve*, *understanding*, *knowledge* and *good.* Overall, the e-learning prototype were able to show an improved academic performance of the student and address different academics and social problems and allow students to study anywhere, at their own convenience whenever online learning is possible and accessible.

Keywords: Reversed Wheel Roulette Selection, personalized learning sequence, reinforcement learning, mastery learning, assessments, performance matrix.

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Abbreviations and Acronyms

ANN	-	Artificial Neural Network
CAT	-	Computer Adaptive Testing
CSE	-	Computer Summative Examination
FIRT	-	Fuzzy Item Response Theory
GA	-	Genetic Algorithms
IRT	-	Item Response Theory
ML	-	Mastery Learning
MLE	-	Maximum Likelihood Estimation
PEL-IRT	-	Personalized E-Learning Item Response Theory
PLS	-	Personalized Learning Sequence
QAO	-	Quality Assurance Office
QIA-UK	-	Quality Improvement Agency of United Kingdom
RL	-	Reinforcement Learning
RWSA	-	Roulette Wheel Selection Algorithm
USA Dep. Ed.	-	USA Department of Education

Definition of Terms

The following definitions are either adapted from existing studies or formulated by the authors based on the prototype implementation, intention and its operational description.

Cognitive Style

Cognitive styles refer to the preferred way an individual processes information. (Dunn & Dunn, 1999).

E-Learning:

E-learning is the use of computer and internet technologies to deliver a broad array of solutions to enable learning and improve performance (Rosenberg, 2000).

Fitness Function (fv):

A fitness function *fv*, is a particular type of objective function that is used to summarize, as a single figure of merit, how close a given design solution is in achieving the set aims (Back, 1996).

Item Bank:

This refers to the database that stores the 12 questions types with 280 questions used for various assessments.

Mastery Learning (ML):

Mastery learning is a learning model which varies instructions according to the aptitude of the students. This results to a higher level of learning by letting the students repeat the assessment until they can achieve the required level of competence (Bloom, 1971).

Lesson:

Refer to the list of chapters of the curriculum vector also know as chromosomes in the study or member of the populations.

Learning Modalities

Refer to sensory preferences that influence the ways in which student learn through visualization, auditory and tactile style (Barbe, Swassing & Milone, 1979).

Learning Style

An individual's unique approach of gaining knowledge, preferred as best method.

Personalized Learning Sequence (PLS):

Personalized learning sequence or PLS is the list of an individualized course structure for each student and is done by dynamically selecting the most optimal teaching operation (Huang, Huang & Chen, 2007).

Reinforcement Learning (RL):

It is a type of learning process which is used to motivate learners to continue the learning process by giving them rewards or points for their efforts or by enforcing punishments when the students cannot pass the learning assessments. (Mataric, 1994; Chen, 2006).

Reversed Roulette Wheel Selection Algorithm (reversed RWSA):

Reversed Roulette Wheel Selection Algorithm is a kind of algorithm which is a combination of a typical RWSA and linear ranking selection that lessens the bias and is implemented in a reversed manner. The lower the fitness value, the more chances lesson will be selected for recombination process.

Roulette Wheel Selection Algorithm (RWSA):

Roulette Wheel Selection algorithm is the simplest of the selection algorithms and most commonly employed for optimization because of its adaptive and heuristic search capability (Kurma, 2012; Sharma, Garg & Sharma, 2013).

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Chapter 1: Introduction

The beginning is the most important part of the work.

Plato(428 BC)

There are two mistakes one can make along the road
to truth… not going all the way, and not starting.

Buddha(480 BCE)

There is no abstract art. You must always start with
something. Afterward you can remove all traces of reality.

Pablo Picasso (1881 - 1973)

1.1 Background of the Study

E-learning is the use of computer and internet technologies to deliver a broad array of solutions to enable learning and improve performance (Rosenberg, 2000). Numerous and countless reports, studies and surveys have shown that e-learning industry isn't showing of slowing down. In fact, an increasing number of institutions, corporations, individuals are recognizing its convenience and its effectiveness. The global e-learning market will reach $107 billion by the end of 2015 (eLearning Industry, 2015). It is inevitable then, that the benefits of e-learning have become widespread and have increased rapidly. This is a trend that is to continue since the concept "learning for life" is an initiative that is actively promoted by governments, educational institutions and research organizations (Lynch, 1999).

In ordinary circumstances, e-learning is self-paced learning activities delivered on a computer with internet connection and typically presents content in a linear fashion. This is like reading an online book or a manual that supports incremental learning process. E-learning provides learning stimulus beyond traditional learning methodology from textbook, manual, or classroom-based instruction. It offers user-friendly solutions for satisfying continuing education requirements. Instead of limiting students to attend courses or reading printed manuals, students are able to acquire knowledge and skills through methods that are much more conducive to individual learning preferences. Furthermore, it offers visual learning benefits through multimedia which are not typically offered by any other methods. It is good alternative to printed learning materials since rich media, including videos or animations, can easily be incorporated to enhance the learning process (Packam, Jones, Miller & Thomas, 2004). However, as e-learning evolved and became the fastest technology in education, many issues have emerged and have continually adapted to the ever-changing needs of learner which were driven by continuous innovation and fast-paced technology development, hypermedia and e-pedagogical strategy.

As a self-paced learning environment, e-learning poses challenges in pedagogical perspective such as how to motivate the students to continue learning in the absence of human instruction. Moreover, it also answers questions on how e-learning system will cater to individualization and personalization to maximize learning process and how it will remediate learning difficulty. According to Huang, Huang and Chen (2007), a learner can take responsibility of his or her own learning and be allowed to personalize his or her own learning path. Another issue that needs to be addressed is the dynamism of students considering their various and different prior knowledge, learning level, age, experiences, goals, learning style, cultural backgrounds and individuality (Brusolovsky & Vassileva, 2003).

Personalizing learning path enables the dynamic insertion, customization or suggestion of content in any format that is relevant to the individual user, based on the user's implicit behaviour and preferences, and explicitly given details (UNESCO, 2012). It is a practical and flexible way to achieve specific education and professional development goals at the learner's own pace. Various approaches to personalize learning path or topic sequencing have been explored in the area of e-learning implementations. The work of Dwi and Basuki (2012) recommended a personalized learning path using feedback, knowledge level and material difficulty. Furthermore, Ballera and Musa (2011), Chen, Chang, Liu and Chiu (2005), Hovakimyan and Sargsyan (2003), made use of personalized e-learning module through learning style, genetic algorithm and item response theory. The work of Papanikolou and Grigoriadou (2002), on the other hand, manipulated the sequence of problems among learners simultaneously while Chang and Lai (2005) and Chen, Lee and Chen (2005) were able to sequence several kinds of teaching operations such as presentations, examples and assessments. It can be said then that personalized learning sequencing is a popular and excellent technology for web-based education.

The idea of personalized learning sequencing or PLS is to generate an individualized course structure for each student by dynamically selecting the most optimal teaching operation. Optimal teaching operation is an operation that brings the students closest to the learning goal within the context of other available operations. Most often, the goal is to learn a required knowledge up to a specific level and to minimize errors in a minimal amount of time. According to Hong, Chen, Chan, Chen (2006) there is no fixed learning paths appropriate for all learners. Success depends on the system capability to automatically adapt the learning material to the student's educational needs to promote learning performance (QIA – UK, 2008). The findings of the experimental study of Guskey (2007) and Wang (2012) showed that the effectiveness and achievements in personalized learning mode were higher, in comparison to the non-personalized learning mode.

To perform personalization, a selection algorithm called Roulette Wheel Selection or RWSA is employed to compute the fitness function. RWSA algorithm is the simplest of the selection algorithms and most commonly employed for optimization and approximations because of its adaptive and heuristic search capability (Kurma, 2012; Sharma, Garg & Sharma, 2013). It inherited some property of genetic algorithms and commonly used for selection and recombination process for small populations. Dynamic fitness value can be collected to create a single numerical value. The computed fitness function produced by RWSA can personalized learning sequence (PLS) or course structure. The course structure is an individualized list of topics or lessons based on student prior performance matrix. Further, the RWSA algorithm can be easily manipulated or modified to cater personalization process. Although, personalized learning sequence have been successfully implemented based on the related literature, RWSA has never been implemented in this area. In addition, based on priori, upon successful implementation of PLS, only few studies continue to mastery and reinforcement learning to remediate learning difficulty.

Mastery learning (ML) is one notable area of educational technology that has attracted much attention in the past. The work of Bloom (1968) on mastery learning is regarded as the classic theoretical perspective with its comparison of two models of education: the traditional model and mastery model. The traditional model uses the same instruction for an entire class, regardless of aptitude. The instructor presents the required information to the students who are then tested to measure the information they have retained. Students are typically given only one chance to learn the material. The course then moves on to the next material. Once tested, students may learn what mistakes they made, but tests are never conducted again to find out whether they have learned from those mistakes. Consequently, the amount of learning in a classroom varies among students. Students with an aptitude to learn requisite materials quickly move forward while slower students fall behind and received lower grades. In contrast, the mastery model varies instructions according to aptitude which results to a higher level of learning for all students. If the students have not learned the material by the first test, they can repeat it until they can achieve the required level of competence. Then they proceed to the next module. As a result, the instructor who employs mastery learning model of education hypothetically achieves high level of learning benefits.

Mastery learning has been widely applied in tertiary and primary levels in a variety of subject matter such as music (Hruska, 2011), economics (Laney, 1999), mathematics (Ma, 2011), skill development and critical thinking (Anderson, 2000). Many meta-analytic studies have demonstrated consistent positive effects of reinforcement and mastery learning (Guskey, 2007; Kulik & Kulik, 2012). The students are helped to master each learning unit before proceeding to a more advanced learning task (Bloom, 1985) in contrast to conventional instruction. If such benefits will likewise be achieved in e-learning, a tremendous impact on the learning process is possible. However, during mastery learning in the form of formative and summative examination, errors, misconceptions and difficulty become inevitable. There is a need therefore to reinforce the learner to repeatedly read and understand the learning materials. The reinforcement should not be similar to the previous lesson, but similar concepts must be taught and applied to avoid boredom and discontinuation of the learning process. This issue should be taken into consideration in designing the e-learning module when a student does self-learning.

The idea of reinforcement learning (RL) is to motivate learners to continue by giving them rewards or points for their efforts or by enforcing penalties when students cannot pass the learning assessments. E-learning is characterized by giving corrective activities to remediate misconceptions or difficulty found during computer summative examination (CSE). It is a principal aid in planning the corrective measures to remedy learning difficulty. For instance, activities to correct these difficulties may involve alternative materials or resources such as videos, simulations, interactive tutorials, scenario-based learning, or any type of learning activity that allow motivational preferences. Reinforcement activities may also include problem-solving exercises, or any learning activities which are stimulating and rewarding to different types of learners. If reinforcement is successful in helping the students by remediating their learning difficulties, then most students will demonstrate readiness to take remedial examination. This can be used as a motivational device in situations where students are shown directly that they can improve their learning and become successful learners.

Reinforcement learning has become a methodology of choice for learning in a variety of domain. Reinforcement learning can be achieved well in games and simulations. The work of Qi (2001), Hu (1998) and O'Doherty (2012) applied reinforcement learning in multi-agent, game-playing environment, and students achieved a superior level of performance in learning complex task. The work of Mataric (1994) used RL to accelerate learning process by giving rewards functions to students. If these benefits can be transformed and then implemented in e-learning, then learning process can be guaranteed.

Educational strategists must develop an e-learning system that personalized learning sequence since learning is dynamic and students are heterogeneous. This e-learning system caters personalization, individualization or customization based on the learner's prior knowledge, prior performance, and study habits. If personalization of learning path and a certain level of competence are achieved, learning benefits such as skills acquisition, knowledge transfer, and increase cognition are also guaranteed.

1.2 Statement of the Problem

Many researchers in the field of personalized learning or topic sequencing have proposed and implemented various mechanisms to improve learning process with the main objective of maximizing learning (Wang, Wang & Huang, 2008; Yang & Wua, 2009; Wang, 2012) and dynamically selecting the closest teaching operation to achieve the learning goals (Chen et al. 2005; Chen & Duh 2008). However, despite recommending a personalized learning sequence, e-learning instructional strategists have failed to perform or address corrective measures to remediate learning misconceptions or errors immediately.

There are many studies and theories to this date that adapted or explains personalization process such as ant colonization (Semet, Lutton & Colett, 2003; Wang et al. 2008), item response theory (Chen, Liu, & Chang, 2006), case based reasoning or CBR (Huang, Huang & Chen, 2007), fuzzy logic (Chen et al. 2008), neural network (Baylari & Monatzer, 2009), genetic algorithm (Huang, Huang & Chen, 2009), multi-level personalization technique (Ballera & Musa, 2010) and material difficulty (Dwi et al. 2012). These studies are algorithmically expensive and complex due to various considerations such as data extractions, involvement of mathematical functions, multi-processes or multiple stages. There are also issues of biases and exactness or correctness of the personalized learning path.

As e-learning materials continue to evolve and increase tremendously in educational setting, it is inevitable that an alternative, more realistic, simpler and a real time multi-based performance for a personalized learning sequence technique should be developed and implemented in e-learning system. Additionally, this research combined the concept of reinforcement learning in the area of artificial intelligence and mastery learning in the area of educational psychology to remediate learning difficulty and improve learning output. The process of personalization, mastery and reinforcement learning and how these three concepts work and improve learning process is demonstrated by actual working prototype.

1.3 Aim

The idea of a personalized learning sequence is to generate an individualized course structure for each student by selecting the most optimal teaching operation (Chen et al. 2005). The aim of this study is to create a personalized learning sequence based on fitness value and perform mastery and reinforcement learning that improves the learning process and increase learning benefits.

1.4 Research Objectives

i. To formulate the fitness criteria of the Roulette Wheel Selection algorithm that personalizes the learning sequence;

ii. To develop a reinforcement and mastery learning model for a personalized learning sequence;

iii. To create an e-learning prototype that personalizes the learning sequence using the fitness function and;

iv. To demonstrate the perceived learning benefits of the e-learning prototype.

1.5 Research Questions

i. How can a fitness function for the roulette wheel selection algorithm to personalize learning sequence be formulated?

ii. How can a reinforcement and mastery learning model for personalized learning sequence be developed?

iii. How can an e-learning prototype that personalizes learning sequence using the fitness function be created?

iv. How can the perceived learning benefits of the e-learning prototype be demonstrated?

1.6 Assumptions

i. Lessons, number of files, videos, animations, PowerPoint presentations, PDFs, documents and other file formats as well as presentations, number of questions both for formative, summative and cognitive examination are sufficient for the study.

ii. Dynamic or populated data collected during the learning process are not the same. Therefore individual data of student are not the same.

iii. The recommended number of reinforcement files vary due to rule-based punishment and reward system employed by the reinforcement and mastery learning architecture. The rules depend on the number of reinforcement files available.

iv. The results obtained in the experiments are not the same under the same computing environment.

v. The analysis of both qualitative and quantitative data and the size of respondents is enough to generalize the conclusions.

vi. The stop criterion of the reinforcement learning is sufficient enough to make conclusions based on the results of reinforcement process.

1.7 Scope and Delimitations

There are many courses for computer science but for the purpose of developing the prototype, the design and analysis of algorithms, one of the core computer courses that requires mathematical analysis and algorithmic program is taken as subject of the research. The topics included in the course Algorithm in e-learning module have been selected or driven by either the problem's practical importance or by some specific characteristic making the problem an interesting research subject. The following are the topics which are included in the module: algorithm analysis, time complexity, sorting techniques, searching algorithms, string processing, shortest path algorithms, graph problems, combinatorial problems, numerical problems and advance structures. The course is composed of 12 lessons with a passing mark of 75 as stipulated in the course syllabus and approved by the Quality Assurance Office or QAO.

In computing the fitness function of the reversed roulette wheel selection algorithm, three performance parameters have been formulated: examination performance, study performance and review performance of the learner. The three performance matrices are extracted from different tables in the database and combined into a single value called fitness value. The fitness value is compared to random numbers generated by the computer between zero (0) and one (1). A lesson fitness value higher than the random value is eliminated; otherwise it is selected for recombination process. This mechanism is the complete reversal of a typical roulette wheel selection to guarantee that topics with achieved competency level would be eliminated, leaving only topics with difficulty as candidates for recombination and undergo reinforcement and mastery learning.

The recommended personalized learning sequence by the system particularly the reversed RWSA varies according to learner perceived learning difficulty. The Reversed Roulette Wheel Selection algorithm is a heuristic technique used for approximation and optimization algorithms. It is worth mentioning that a solution would be acceptable rather than exact because of its approximation and randomness value. In particular, to find an exact solution for this kind of problem is almost impossible because of the very large set of possible solutions. Considering that no two learners are the same, and that students come from different backgrounds and different knowledge and level, a right solution for a particular learner is therefore difficult to define. Nevertheless, the study attempts to generate a personalized learning sequence based on different performance matrices accumulated during the learning process. The system of personalization and recombination process stops at third iteration level.

During mastery learning, students are numerically rewarded or punished according to the difficulty matrix developed during summative examination. Student who passed are rewarded with numerical points; those who failed are punished by giving them extra course materials for reading, viewing solved problem exercises and practice examinations. The number of additional or alternative learning materials varies accordingly as defined by the rule-based punishment and reward system employed by the reinforcement learning mechanism.

1.8 Significance

It is the hope of this study to encourage an e-learning instructional strategist to implement an e-learning system that can support personalization and mastery learning. Particularly, this study hopes to contribute critically in the development and implementation of e-learning especially within the perspective of Arab and North African countries. The following are some of the significance:

i. *Presents a personalized learning sequence* – There are many tangible and intangible benefits of personalizing the sequence of lessons in the curriculum vector (syllabus). It lessens the time in learning the course materials by skipping some lessons that learners already know, thereby, focusing only on lessons where students commit errors during the summative examination. Since e-learning is self-paced, students have the convenience to study at home and become more productive. In Libya, where majority of the students are women who abide by the Muslim tradition, where the culture is generally patriarchal, and have less opportunity than men, e-learning will give them time to balance their family life and schooling. E-learning is seen as one of the possible solutions to many problems in Libyan academic institutions including factors from political, cultural and social aspects. Politically, during the war and in the presence of security threat, or declared holidays, students were not able to come to the university due to restricted mobility and threat to security and safety. From a cultural perspective also, majority of the university students are women who are basically busy with family commitments and have no time to attend classes. The presence of foreign instructors which can be attributed to two decades of English embargo and who are tasked to deliver information technology also act as barriers to communication. Thus, e-learning can fill in these gaps by allowing students to personalize their course learning materials and study anywhere, at their own time and disposal.

ii. *Provides mastery learning and reinforcement learning* - If the students could not learn the materials by the first test, they can repeat it until they achieve the required level of competence through reinforcement learning. During reinforcement, misconceived or difficult lessons will be re-learned by loading lessons and practice examinations not similar to the previous, but have the same concepts, to avoid boredom in the learning process. Then they can proceed to the next module. As a result, teachers who employ a mastery learning model of education are expected to hypothetically find high levels of achievement among all students.

iii. *Provides learning benefits* – There are many educational benefits of adapting the evolutionary techniques in e-learning implementation. It is hypothetically believed that it will improve or increase the cognitive ability of the students in different stages of cognitive development. Most frequently cited educational benefits include development of critical thinking, self-reflection, acquisition and construction of knowledge and personal confidence.

iv. *Provides pedagogical alternatives* – Since learning styles and pedagogical strategy effectively vary according to the learner, an alternative instructional deign for e-learning system and development is highly recommended. An educational strategist will employ strategy that lessens the learning time without sacrificing the quality of learning benefits, while allowing the students to study wherever, whenever possible. Students can re-learn, practice examination, and develop self-skills and self-learning.

Chapter 2: Literature Review

All truths are easy to understand once they are discovered; the point is to discover them.

Galileo Galilei (1564 - 1642)

The real voyage of discovery consists not in seeking new landscapes but having new eyes.

Marcel Proust (1871 - 1922)

To achieve lasting literature, fictional or factual, a writer needs a perceptive vision, absorptive capacity, and creative strength.

Lawrence Clark Powell (1906 - 2001)

2.1 Introduction

In relation to the research objectives stated in the previous chapter, four important concepts have been investigated in current literature which focus on personalization, mastery learning, reinforcement learning and e-learning design as shown in Figure 2.1. First, current trends on personalization were reviewed and three selection algorithms were investigated to determine the fitness function of a lesson. Second, the researcher studied the effect of mastery learning, a notable area in educational psychology focusing on achieving competency. Third, the reinforcement learning in the area of supervised learning of artificial intelligence and its impact to e-learning implementation was looked into and analyzed. Lastly, the design of e-learning system that focuses on cognitive development composed of multimedia elements, the use of simulations and interactivity, the use and impact of different learning theories in e-learning implementation and assessment mechanism were also examined.

For the purpose of discussion and establishing convincing literature that would strengthen the thesis idea, Figure 2.1 serves as a framework in studying the related literature. The end of this chapter is a synthesis which establishes the gap of the current literature and what new ideas can be explored which lead to the development of the conceptual framework of the study.

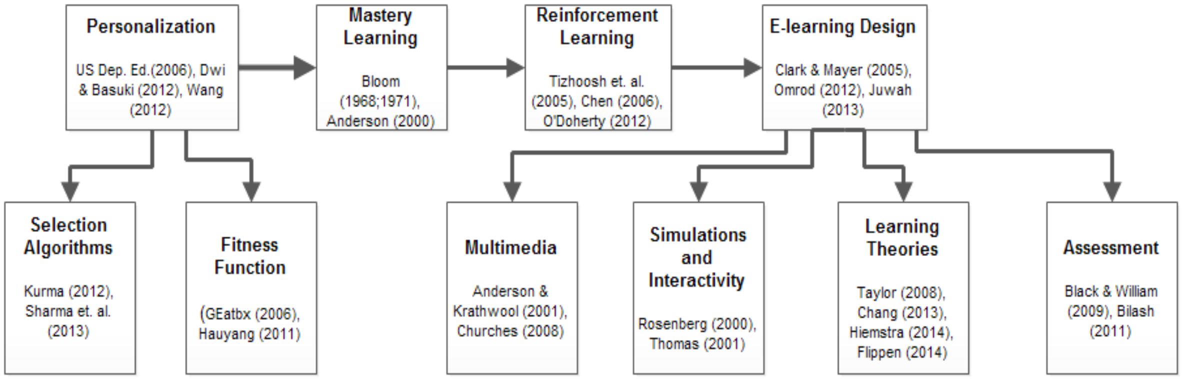


Figure 2.1. Summary of Literature Review

2.2 Personalized Learning

The proliferation of internet and graphics-rich learning material has changed the experiences, attitudes and expectations of the learners, challenging traditional method of teaching. Learning is too focused on the teacher or the content. Expert pedagogical strategists attempt to transfer knowledge by means of lectures, textbooks or online text which are then followed by an assessment. Presky (2001) refers to this as “tell-test education”, and states that these methods are not totally successful because learners’ skills are also changing. At present, there is a need to focus on individual or personalized learning path.

Personalized learning has been defined in various ways by the experts of pedagogical strategies. According to the National Educational Technology Plan developed by the US Department of Education (2009), personalized learning is defined as adjusting the pace, adjusting the approach, and connecting to the learner’s interest and experiences to increase learning output. Moreover, personalized learning is the process of designing learning to specific individuals, recognizing that learners have different strengths and weaknesses, interests and ways of learning. Everyone has to learn different things, although eventually individual interests take learners into different directions. Personalized learning is the most suitable method in finding out what individual learners want to engage in terms of their interests, passions and ways of thinking (Robinson, 2011). Bray and McClaskey (2012) assert that learners should understand how they best to perform so they become active in designing their learning goals. The learners express what they know and how they engage with the content. This is because when students take responsibility of their learning, they are more motivated and engaged in the learning process.

Recently, the growth of web-learning systems have stimulated various research on personalized and individualized learning opportunity which is suitable to heterogeneous learners if their needs and preferences would be considered. One of these personalized techniques is the work of Dwi and Basuki (2012) where the course material sequence is modified according to the learner's knowledge, feedbacks, and material difficulty levels. The knowledge level is obtained from the analysis of pre-test result, while feedback is acquired through questionnaire after the learners have finished a learning unit. After the students have given feedbacks, the system then modifies the difficulty level of the corresponding learning unit to update courseware material sequencing. The difficulty level initially were the same at a levelling stage but dynamically change to each student as it collects feedback and pre-test score. For example, if the feedback is perceived to be difficult and the pre-test is low, then the learning sequence will change accordingly based on its difficulty level score. Learning materials with high difficulty level will less prioritized as it will be read last in the learning sequence. Findings of the experimental study show that the effectiveness and achievements in personalized learning mode are higher in comparison to the non-personalized learning mode.

Personalized learning sequence is an important research issue for web-based learning systems because no fixed learning paths are appropriate for all learners (Chen, Hong, Chan & Chen, 2007). The idea is to create an individualized course for each student by applying the computerized adaptive testing (CAT), computing the curriculum difficulty parameters and estimating the curriculum difficulty. The genetic algorithms approach can generate a personalized curriculum sequence and then employ case-based reasoning to perform corrective activities (Huang, Huang & Chen, 2007). Experimental results indicate that applying the proposed genetic-based personalized e-learning system for web-based learning is more effective than the free browsing learning mode because of its high quality and concise learning path for individual learners. The approach generates a personalized sequence based on the individual learner's requirements, and helps them to learn effectively in a web-based learning environment. Although successful, this approach is algorithmically expensive in programming and has limited samples in e-learning course. Personalized learning is an alternative to the traditional "one size fits all" approach and has developed the growth of teaching and learning towards a dynamic learning process. Therefore, exploring adaptive paths to suit the learners' personalized needs is an essential issue. The work of Wang, Wang and Huang (2008), for example, used the ant colony optimization, a recent meta-heuristic method for discovering group patterns that is designed to help learners advance their on-line learning along a personalized learning path. The investigation emphasizes the relationship of the learning content to the learning style of each participant in personalized or adaptive learning. An adaptive learning rule was developed to identify how learners of different learning styles may associate those contents which have the higher probability of being useful to form an optimal learning path. A style-based ant colony system is implemented and its algorithm parameters are optimized to conform to the actual pedagogical process. A survey was also conducted to evaluate the validity and efficiency of the system in producing adaptive paths to different learners. The results revealed that both the learners and the lecturers agree that the style-based ant colony system is able to provide useful supplementary learning paths.

According to Yang and Wua (2009); and Wang (2012), in recommending appropriate personalized learning path or personalized materials for a certain learner, several characteristics of the learners, such as their learning styles, learning modalities, cognitive styles and competencies, need to be considered. Their work shows that a fuzzy knowledge extraction model can be established to extract a personalized and recommended a knowledge by discovering effective learning paths based on the past learning experiences through the ant colony optimization model. Though the results revealed that the theoretical potential of the proposed method in discovering effective learning paths for learners, critical limitations arose in considering its applications to real world situations. Such considerations include a large number of learners and a long period of training cycles to discover good learning paths for learners.

E-learning has become a major development in the computer assisted teaching and learning field. Many researchers maximize the potential of e-learning systems with personalized learning mechanism to aid on-line learning. However, most systems focus only on using the learners' behaviors, interests, and habits to provide personalized e-learning services. These systems commonly failed to consider the suitability of the learners' ability and the difficulty level of the recommended courseware. Unsuitable courseware cause learners' cognitive overload or disorientation during learning. Moreover, to promote learning effectiveness, Chen et al. (2008) proposes a personalized e-learning system based on the item response theory (PEL-IRT), which can consider both the difficulty of the course material and the learners' ability which are evaluated by the learners' crisp feedback responses (i.e. completely understanding or not understanding answer) to provide personalized learning paths for individual learners. The PEL-IRT, however, cannot estimate the learners' ability for personalized learning services based on the learners' non-crisp responses (i.e. uncertain/fuzzy responses). The main problem is that learners' responses do not usually indicate complete understanding or do not understand the content of the learned courseware. Therefore, the study developed a personalized learning system based on the proposed fuzzy item response theory (FIRT), which is capable of recommending a courseware to suit the difficulty levels of the learners based on the learners' uncertain/fuzzy feedback responses. The FIRT can correctly estimate learners' ability via the fuzzy inference mechanism and revise the estimated function of the learners' ability while the learner responds to the difficulty level and comprehension percentage of the learned courseware. Moreover, a courseware modeling process based on a statistical technique to establish the difficulty parameters of courseware for the proposed personalized learning and tutoring system was developed by the study. Experimental results indicated that by applying the proposed FIRT to a web-based learning, better learning services can be provided to individual learners compared to what was developed by the PEL-IRT. This helps the students learn more effectively.

In web-based educational systems, the structure of learning domain and content are usually presented in the static way, without taking into account the learners' goals, their experiences, their existing knowledge, their ability, and their non-interactivity (Ballera & Elssaedi, 2013). Generally, the process of instruction completes the assessment and it is used to evaluate the learners' learning efficiency, skill and knowledge. But in web-based educational systems less attention on adaptive and personalized assessment is given. Considering the importance of tests, a personalized multi-agent e-learning system based on item response theory (IRT) and artificial neural network (ANN) which presents adaptive tests (based on IRT) and personalized recommendations (based on ANN) were used. These agents add adaptively and interactivity to the learning environment and added the human dimension of instruction. This guides the learners in a friendly and personalized teaching environment (Baylari & Monatzer, 2009).

Personalized learning service is important on the internet-based education due to the absence of instructor. However, the learner's ability usually is neglected as an important factor in implementing personalized mechanisms. Besides, too many hyperlink structures in web-based learning systems become a burden to learners because of the huge amount of information (getting lost in hyperspace), cognitive overload and lack of an adaptive mechanism. Information overload have becomes the main issues in web-based learning. The work of Chen, Lee and Chen (2005) and Chen, Liu, and Chang (2006) proposed a personalized e-learning system based on Item Response Theory and maximum likelihood estimation (PEL-IRT-MLE) which considers both the difficulty of the course materials and the learners' ability to provide individual learning paths for students. To obtain more precise estimation of the learners' ability, the maximum likelihood estimation (MLE) is applied to estimate their ability based on the explicit learner feedback. Moreover, to determine the appropriate level of difficulty parameter for the course materials, the study also used a collaborative voting approach for adjusting the difficulty of the course material. Experiment results shown that applying item response theory (IRT) to web-based learning, it can achieved personalized learning and helped students to learn more effectively and efficiently.

Various studies on personalized learning have been investigated and implemented, creating a dynamic, learner-centered structure of learning. It can be said that personalizing learning sequence is an excellent technology for e-learning. However, there are still many possible techniques and strategies which can be done to improve e-learning implementation. If a new alternative can be developed to provide learning benefits mentioned above, and which can be implemented simply, then this alternative becomes acceptable as an excellent choice to personalize learning.

2.2.1 Selection Algorithm Analysis

In order to determine how to optimize the populations and how it could be used to provide alternative personalized learning path, three selected algorithms were studied. These selection algorithms is needed to understand and then establish an optimize solution, capable of generating a PLS. In the process of selection, the offspring producing individuals are chosen. The first step is fitness assignment. Each individual in the selection pool receives a reproduction probability depending on the fitness value and the fitness value of all other individuals in the selection pool. In this section, three selection algorithms have been studied and investigated.

2.2.1.1 Roulette Wheel Selection Algorithm

A Roulette Wheel Selection algorithm is the simplest selection scheme. Also called the fitness proportionate selection algorithm, it is one of the notable selection algorithms used in genetic algorithms as a genetic operator for selecting potentially useful solutions for optimization, re-combinations and supervised learning (Kurma, 2012; Sharma, Garg & Sharma, 2013).

ALGORITHM *Roulette Wheel Selection Algorithm*

1. $S \leftarrow 0$;// Computing the fitness function
for $i \leftarrow 1$ **to** N **do** compute (FV_i)
$S = S + FV_i$

2. **for** $i \leftarrow 1$ **to** N **do** //compute the cumulative FV
compute cumulative FV (cFV_i)

3. generate random number **r** from interval (0,S)

4. **for** $i \leftarrow 1$ **to** N **do** **//**eliminating weak chromosomes
if $r_i \leq cFV_i$, select L_i
return $\{L_i, L_{i+1}, \ldots, L_N\}$

Figure 2.2: Typical Roulette Wheel Selection Algorithm

Figure 2.2 describes how a roulette wheel selection works. The fitness level is used to associate a probability of selection of each individual. The individuals are mapped according to contiguous segments of a line, such that each individual's segment is equal in size to its fitness. A random number is generated and the individual whose segment spans the random number is selected. The process is repeated until the desired number of individual is obtained. This technique is analogous to a roulette wheel with each slice proportional to the fitness value. This mechanism is similar to a roulette wheel in a casino. Usually, a portion of the wheel is assigned to each of the possible selections based on their fitness value. This can be achieved by dividing the fitness of a selection by the total fitness of all the selections, thereby normalizing them to one. A random selection is made similar to how the roulette wheel is rotated (Back, 1996).

Table 2.1 shows the selection probability for 11 individuals together with the fitness value. Individual 1 is the most fitted individual and occupies the largest interval, whereas individual 10 is the second least fitted individual which has the smallest interval on the line. Individual 11, the least fit interval, has a fitness value of 0 and gets no chance for reproduction. Interval refer to range or chunk of a normalized value that define the scope of an individual based on its fitness value. For example, individual 1 in Table 2.1 has an interval of 0 to .18 while individual 2 is .19 to .34, individual 3 has an interval of .35 to .49 and so on until it reach the normalized value of one. Normalized value means that the cumulative sum of the selection probability is always equal to 1, otherwise an error in normalization occur.

Table 2.1: Selection Probability and Fitness Value

Number of Individual	1	2	3	4	5	6	7	8	9	10	11
Fitness Value	2.0	1.8	1.6	1.4	1.2	1.0	0.8	0.6	0.4	0.2	0.0
Selection Probability	0.18	0.16	0.15	0.13	0.11	0.09	0.07	0.05	0.03	0.02	0.0

In selecting the next population, the appropriate number of uniformly distributed random numbers (uniform distributed between 0.0 and 1.0) is independently generated. Applying sample of 6 random numbers: 0.81, 0.32, 0.96, 0.01, 0.65, 0.42, Figure 2.3 illustrates the mapping of the Roulette Wheel Selection algorithm, applying the six generated random numbers that resulted to the sequence of 1, 2, 3, 5, 6, 9. The solutions with a higher fitness will be less likely to be eliminated, however, there is still a chance that they may be selected for the next generation. With fitness proportionate selection, there is a chance that some weaker solutions may survive the selection process; this is an advantage, because although a solution may be weak, it may include some components which can prove useful in following the recombination process. Weaker individuals are not without a chance. In nature, such individuals may have genetic coding that may prove useful to future generations. The roulette wheel selection algorithm provides a zero bias and does not guarantee minimum spread.

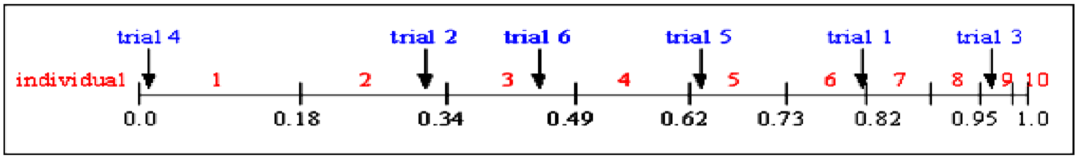


Figure 2.3: Roulette Wheel Selection (Source: GEATbx, 2006)

2.2.1.2 Truncation Selection Algorithm

Compared to the previous selection methods, the truncation selection method is an artificial selection method. It is used by breeders for large population or mass selection. In truncation selection, individuals are sorted according to their fitness. Only the best individuals are selected for the parents. The parameter for the truncation selection is the truncation threshold *Trunc*. *Trunc* indicates the proportion of the population to be selected as parents take values ranging from 10% - 50%. Individuals below the truncation threshold do not produce offspring. The term selection intensity is often used in truncation selection. Table 2.2 shows the relation between *Trunc* and selection intensity.

Table 2.2: Truncation Threshold and Selection Intensity (Source: GEATbx, 2006)

Truncation Threshold	1%	10%	20%	40%	50%	80%
Selection Intensity	2.66	1.76	1.2	0.97	0.8	0.34

Equation 2.1: Selection Intensity is defined as the average fitness of the population after selection and which assumes an initial normalized Gaussian distribution G(0,1).

$$SelectIntTrunc = \frac{1}{Trunc}.\frac{1}{\sqrt{2\pi}}.e\frac{f_c^{\,2}}{2} \qquad \textbf{(2.1)}$$

Equation 2.2: Truncation Loss of Diversity is a selection method that selects the fraction *Trunc* of the population.

$$LossDivTrunc = 1 - Trunc \tag{2.2}$$

Equation 2.3: Selection Variance for Truncation is described as difference of 1 and selection intensity times the intensity minus the truncation threshold.

$$SelectVar(\mathrm{Trunc}) = 1 - SelectInt(Trunc)\ \mathrm{x}\ SelectInt(Trunc) - f_c \tag{2.3}$$

Muhlebein and Schlierkamp-Voosen (1993) introduced this selection scheme to the domain of genetic algorithms. In the truncation selection, the candidate solutions are ordered according to fitness, and some proportion, *p*, (e.g. p=1/2, 1/3, etc.) of the fittest individuals are selected and reproduced 1/p times. Although this method has been studied several times by Back (1995), Blickle and Thiele (1995), Muhlenbein and Voight (1995), this selection method is less sophisticated compared to other selection methods, and is not often used in practice.

2.2.1.3 Tournament Selection Algorithm

The tournament selection technique is a stochastic universal sampling often used in practice (Harik, Paz, Miller & Goldberg, 1999; Huayang & Zhang, 2011). This is because it has less stochastic noise, fast, easy to implement, and has a constant selection pressure (Blickle et al., 1995). Goldberg and Deb (1991) used the tournament selection in a number *Tour*, of individuals chosen randomly from the population. The best individual from this group is selected as a parent. This process is repeated as often as possible until individuals are chosen. These selected parents produce uniform at random offspring. Selection pressure is easily adjusted by changing the tournament size. If the tournament size is larger, weak individuals have a smaller chance to be selected. The parameter for tournament selection is the tournament size, *Tour*. *Tour* takes values ranging from 2 to *Nind* (number of individuals in population). Table 2.3 below shows the relation between the tournament size and the selection intensity.

Table. 2.3: Relation between tournament size and selection intensity

Tournament Size	1	2	3	5	10	30
Selection Intensity	0	0.56	0.85	1.15	1.53	2.04

Equation 2.4: Tournament Selection Intensity is described as the square root of the given constant as selection variance increases and selection intensity increases the truncation selection decreases.

$$SelectInt(Tour) = \sqrt{2\ln(Tour) - \ln\sqrt{4.14(\ln(Tour))}} \qquad \textbf{(2.4)}$$

Equation 2.5: Tournament Loss of Diversity guaranteed that 50% of the population with tournament size Tour=5 is eliminated.

$$LossDiv(\mathrm{Tour}) = \mathrm{Tour}\,\frac{-1}{Tour-1} - Tour\,\frac{-Tour}{Tour-1} \qquad \textbf{(2.5)}$$

Equation 2.6: Tournament Selection Variance is given by the constant formula.

$$SelectVar(Tour) \approx \frac{.918}{\ln(1.1186+1.328(\mathrm{Tour})} \qquad \textbf{(2.6)}$$

Deterministic tournament selection selects the best individual (when p=1) in any tournament. A one-way tournament (k=1) selection is equivalent to random selection. The chosen individual can be removed from the population, otherwise individuals can be selected more than once for the next generation. Figure 2.4 below describes how a truncation selection algorithm works.

ALGORITHM Tournament Selection

1. choose k (the tournament size) individuals from the population at random
2. choose the best individual from pool/tournament with probability p
3. choose the second best individual with probability p*(1-p)
4. choose the third best individual with probability p*((1-p)^2)
   and so on.

Figure 2.4: Truncation Selection Algorithm

The selection pressure of the tournament selection directly varies with the tournament size - the more competitors, the higher the resulting selection pressure. This selection has several benefits: it is efficient to code, works on parallel architectures and allows the selection pressure to be easily adjusted. While tournament selection is often used in conjunction with noisy (imperfect) fitness functions, little is understood about how the noise affects the resulting selection pressure. The work of Miller and Goldberg (1995) quantitatively predicts the selection pressure for tournament selection utilizing noisy fitness functions. Given the tournament size and noise level of a noisy fitness function, it can predict the resulting selection pressure of tournament.

2.3 Mastery Learning

Mastery learning is a theoretical perspective of education that has attracted much attention in the past. Mastery learning was coined by Benjamin Bloom (1968; 1971) and is widely regarded as the classic theoretical perspective in pedagogy. Bloom hypothesized that a classroom which focuses on mastery learning as opposed to the traditional form of instruction reduces the achievement gaps between varying groups of students (Guskey, 2007). In mastery learning, the students are helped to master each learning unit before proceeding to a more advanced learning task in contrast to the conventional instruction.

The concept of mastery learning can be attributed to the behaviourism principles of operant conditioning. Operant conditioning theory asserts that learning occurs when an association is formed between a stimulus and a response. In line with the behaviour theory, mastery learning focuses on an overt behaviours that can be observed and measured. The material that will be taught is broken down into small discrete lessons that follow a logical progression. In order to demonstrate mastery over each lesson, students must be able to overtly show evidence of understanding the material before moving to the next lesson (Anderson, 2000). It is based on the concept that all students can learn when provided with conditions appropriate to their situations. The students must reach a predetermined level of mastery in one unit before they are allowed to progress to the next. In mastery learning, students are given specific feedback about their learning progress at regular intervals throughout the instructional period. This feedback helps students identify what they have learned well and what they have not. Areas that are not learned well are allotted more time to achieve mastery learning. Only grades of "A" or "B" are given because these are the accepted standards of mastery. Students must demonstrate mastery in unit examinations, typically with a score of 75, before moving to the next learning materials (Davis & Sorrell, 1995).

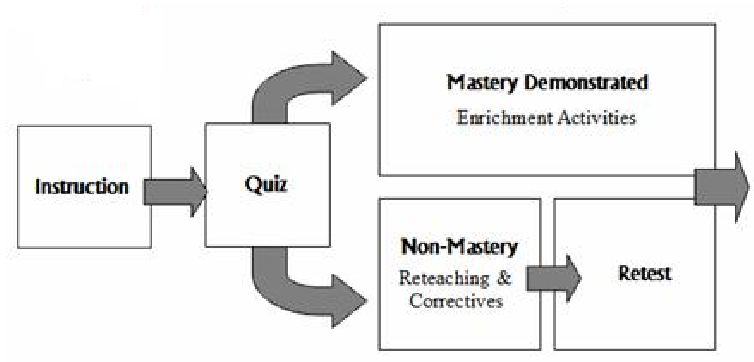


Figure 2.5: Learning Mastery Architecture (Source: Candler, 1996)

The major steps in implementing mastery learning are outlined in Figure 2.5. First, teachers must present instructional materials and determine the level of students who are ready to learn. Second, a quiz or a formative assessment which is basically a diagnostic instrument or process used by the teacher to determine difficulty and as basis for corrective activities to remediate learning errors is planned. Assessment in the mastery learning classroom is not used as a measure of accountability, but rather as a source of evidence to guide future instruction. A teacher using the mastery approach uses the evidence generated from their assessment to modify activities that best serve each student. In this sense, students do not compete against each other, but rather compete against themselves in order to achieve their personal best. Third, activities which correct and enrich may take a variety of forms and usually vary from one unit to the next. For instance, activities which correct may involve alternative materials or resources, peer tutoring, computer assisted lesson, interactive demos and simulations or any type of learning activity that are both stimulating and rewarding for fast learners at varying degree. Students will receive constructive feedback on their work and will be encouraged to revise and revisit their work until the objective is achieved. Finally, a second assessment is formed to determine mastery based on the corrective activities. It covers the same concepts and materials like the first assessment but ask questions in a slightly different way or format. If the corrective activity is successful in helping the students remedy their learning difficulties, then almost all students will demonstrate mastery in the second formative assessment. The second assessment or retest becomes a powerful motivational device in directly showing to the students that they can improve their learning and become successful learners (Bloom, 1971). In the process, the students can move on to the next unit of instruction.

Mastery learning has been widely applied in tertiary and primary education, adult learning, training, instructional learning models and in a variety of subject matters such as in the fields of mathematics (Gomez & Sangel, 2012), nursing (Bender, 2007; Roberts, Ingram & Flack, 2012), physics (Wambugo & Changeyiwo, 2008), and for skills such as reading (Crijnene Feehan & Kellan, 1998) and critical thinking (Anderson, 2000; Hmelo, 2009). Many meta-analytic studies have demonstrated consistent positive effects for mastery learning programs.

In general, studies have shown that mastery learning programs result to higher achievement in all students as compared to the more traditional forms of teaching (Anderson, 2000). Despite the empirical evidences, many mastery programs in schools have been replaced by more the traditional forms of instruction because of the level of commitment required from the teacher and the difficulty in managing the classroom especially when each student follows an individual course of learning. Despite the conclusive evidence that an appropriately instituted mastery approach to instruction yields improvement in students' achievement, criticisms such as time constraints as a flaw in the approach often surface. Educators who prefer breadth of knowledge rather than depth of knowledge may feel that it is more important to "cover" a lot of materials than to focus on details. They also focus their energy in ensuring that all students achieve learning goals. Many teachers are hesitant to institute a mastery learning approach in their classroom because of fear that they may not finish the lessons' coverage on time. Giving students extra time in completing their work is also viewed as unfair by some critics. They argue that differentiated instruction is inherently unfair because students who receive extra feedback and time are somehow given an advantage over students who achieve the objectives of the lesson. Most of these criticisms stem from a misunderstanding of Bloom’s approach. In Bloom’s ideal classroom, the institution of a mastery learning approach is postulated to eventually lead to a drastic decline in the variation of student achievement, as students who require more correctives initially and evidently gain personal benefits from the process. The students eventually come to employ these varying strategies and techniques on their own. On the other hand, students who receive less will make slower progress. As the gap in student achievement lessens, more time will be devoted to "enrichment activities" rather than corrective activities for all students (Guskey, 2007).

2.4 Reinforcement Learning

Reinforcement learning is a learning paradigm which aims to control a system so as to maximize the numerical performance measure that expresses a long-term objective. Reinforcement learning provides partial feedback and provides predictions when to implement the learner’s corrective activities. It can be described as an intelligent technique in learning achieved by interacting with the environment (Sutton & Barto, 1998). In reinforcement learning technique, the agents map the states of the environment to appropriate actions in order to maximize rewards (Ayesh, 2004). Reinforcement learning is of great interest because of the large number of practical applications that can be used to address problems in artificial intelligence, in operations research or control engineering and in learning.

Advanced computer systems have become pivotal components for learning. However, there are still many challenges in e-learning environments when developing reliable tools to assist users and facilitate and enhance the learning process. For instance, the problem of creating an e-learning system that can be learned from interaction, learning the students’ preferences, and increasing learning efficiency of individual users are still widely unsolved. Reinforcement learning (RL) is an intelligent technique that can be learned from trial and error mechanism and generally does not need any training data or a user model. At the beginning of the learning process, the RL does not have any knowledge about what actions it should take. After a while, the RL learns which actions need to be taken and which yield the reward. The ability of learning from interaction with a dynamic environment and using reward and punishment independent from any training data sets makes reinforcement suitable tool for e-learning situations where subjective user feedback can easily be translated into reinforcement signal.

Figure 2.6 models the agent in the environment and how it chooses an action a_i, obtains reward r_i, and switches from state s_i to state s_{i+1}. The goal is to maximize the long term reward, where γ is called the discounting factor. The RL has become the chosen methodology for learning in a variety of domains. RL is played well in games and simulation (Hu & Wellman, 1998; Qi, 2001; O'Doherty, 2012). Educators apply reinforcement learning in multi-agent and game-playing environment to achieve a superior level of performance in learning complex tasks. It accelerates the learning process by giving the rewards functions (Mataric, 1994). The RL agent or the decision-maker takes the action by using a policy to influence the state of the environment. Reinforcement feedback provides knowledge on the actions which manifested through rewards or punishments. The agent learns to take the actions that are most rewarding in order to reach its goal.

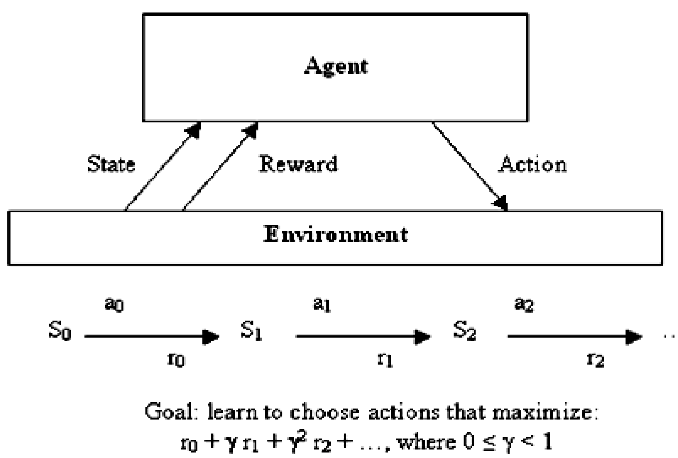


Figure 2.6: Standard Model of Reinforcement Learning (Chen, 2006)

Literatures that focus on user-machine interface and the complexity of a dynamic environment like the e-learning application reveal that it is based on reinforcement learning. In e-learning application, the user needs access to the most suitable sources of information. Reinforcement learning has the ability to autonomously lead search engines to adapt themselves by monitoring the user's queries, reaction to messages, and even actions that the user takes examination. As a consequence, an intelligent search engine can improve its behavior in order to personalize search tools, save the user's time and avoid confusion and fatigue by providing the shortest path to the optimal learning object. Some hybrid systems using reinforcement learning technique are provided by presenting the states and actions and defining the objective and subjective reward such as the area of image-based application. The high and low-level image processing techniques must be applied to extract features, patterns and clues from an image set or a single image (MacArthur & Bradley, 2000).

In the framework of e-learning, various research show the design of an artificial intelligent system to provide services for the learner through the web or other interfaces. Intelligent agent should act rationally in performing a task for the user and in reducing human error or fatigue. Reinforcement learning can be employed to design a personalized system to adapt to human intention, intuition, needs, and requests. To design an adaptive personalized mechanism, the artificial intelligent system must communicate with the user through the graphical user interface (GUI). Requests, responses, and reactions can be given by the users to the computer by using intelligent GUI. This yields the most efficient system that can perform challenging tasks, save the user's time and prevent user fatigue and confusion. The work of Tizhoosh, Shokri and Kamel (2005) accomplished this by linking AI and GUI in order to have a flexible interaction strategy that contributes in determining what is best suited for the most appropriate time for the learner.

2.5 E-Learning Design

Designing the e-learning programs can be challenging, but important for effective learning. Learning must be able to motivate hence relevant, engages the users, and allows them to control learning to an appropriate extent. There are many considerations in designing the e-learning system and these include cognitive development, content management, media technology, learning delivery, instructional design and many other details. The following succeeding sub-topics discuss concepts that are adapted in creating e-learning system prototype.

2.5.1 Cognitive Learning in E-learning Design

The design will support the learning theories and will focus on three domains: the cognitive, affective and psychomotor development of the students. Of the three domains, details on cognitive development and how it will be implemented in e-learning design will be exhaustively discussed. Many e-learning designs are available and worthy to be implemented but this study will focus on how cognitive development will be maximized by taking into account factors that involve cognitive activities and development (Clark & Mayer, 2003). The following components can contribute to the cognitive enhancements in e-learning materials; learning theories, interactivity and simulation, and the effect of multimedia learning materials such as video, graphics, animation, and assessment in the overall design of e-learning prototype (Juwah, 2013).

2.5.1.1 Learning Theories

According to Knud (2004) and Ormrod (2012) learning theories are conceptual frameworks that describe how information is absorbed, processed and retained during learning. Cognitive, emotional, and environmental influences, as well as prior experience, all play a part in how understanding, or a worldview, is acquired or changed, and knowledge and skills retained. There are many learning theories which vary accordingly to their implementation and concepts yet all of these are encompassed by four known learning theories in the field of educational technology; behaviourism, constructivism, transformative and cognitivism.

Behaviourism is coined by Watson (Cherry, 2013) in which learning is the acquisition of a new behaviour through conditioning; the operant and classical conditioning. Operant conditioning is the reinforcement of behavior by a reward or a punishment while the latter is a reflex response to stimulus. Behaviourism is found to be excellent in the area of competency-based learning, skill development and training. Educational approaches such as applied behaviour analysis, curriculum-based measurement, and direct instruction have also emerged from this model (Flippen, 2014 p.1; Keesee, 2014; Hiemstra, 2014) .

Constructivism on the other hand, provides context for the learner by placing the learner in a situation similar to the one in which he/she is going to apply the knowledge.

Understanding is more important than memorizing facts. Through the construction of understanding and meaning, the learner interprets and acts upon the material being learned and thereby results to better understanding of the materials. The idea of Piaget and Bruner is to build learning based on new ideas or concepts of the current knowledge and past experience (Keesee, 2014).

Transformative learning theory seeks to explain how human revise and reinterpret meaning (Taylor, 2008). Transformative learning is the cognitive process of effecting change in a frame of reference that defines our view of the world. Emotions are often involved in which adults have a tendency to reject any ideas that do not correspond to their particular values, associations, and concepts. There are three levels of transformation in transformative learning theory: psychological, which means changes in understanding of the self, convictional, which is revision of belief systems, and behavioral, which involves change in lifestyle (Mezirow, 1997; Knud, 2004).

The cognitive learning theory considers how human memory works to promote learning, and understands short term and long term memories. They view learning as an internal mental process including insight, information processing, memory and perception where the educator focuses on building intelligence and cognitive development. Meaningful information is easier to learn and remember. If a learner links a relatively meaningless information to a prior schema then this information will be easier to retain. It is easier to remember items from the beginning or end of a list rather than those in the middle, unless that item is distinctly different. Practicing or rehearsing improves retention especially when it is distributed practice. By distributing practices, the learner associates the material with many different contexts rather than one context afforded by mass practice. These are the effects of prior learning on learning new tasks or material. (Keesse, 2014).

These four learning theories can be combined interchangeably in the learning process. In e-learning for instance, behaviourism is effective in knowledge based, skill acquisition, and training while constructivism is excellent in situational-based learning. Transformative learning on the other hand, is good in proving knowledge, thereby, changing the learner's prior knowledge based on the evidence collected during the learning process, while cognitive is the mental effect of learning, the highest among the four learning theories. In combining these four learning theories, Bloom's Cognitive model can be utilized in the development of the system.

2.5.1.2 Bloom's Cognitive Model

There is more than one type of learning domain. A committee of colleges, led by Benjamin Bloom (1956), identified three domains of educational activities: cognitive, affective and psychomotor. This taxonomy of learning behaviors can be thought of as "the goals of the learning process". That is, after learning an episode, the learner should have acquired new skills, knowledge, and/or attitudes. The cognitive domain of Bloom involves knowledge and the development of intellectual skills. This includes the recall or recognition of specific facts, procedural patterns, and concepts that serve in the development of intellectual abilities and skills.

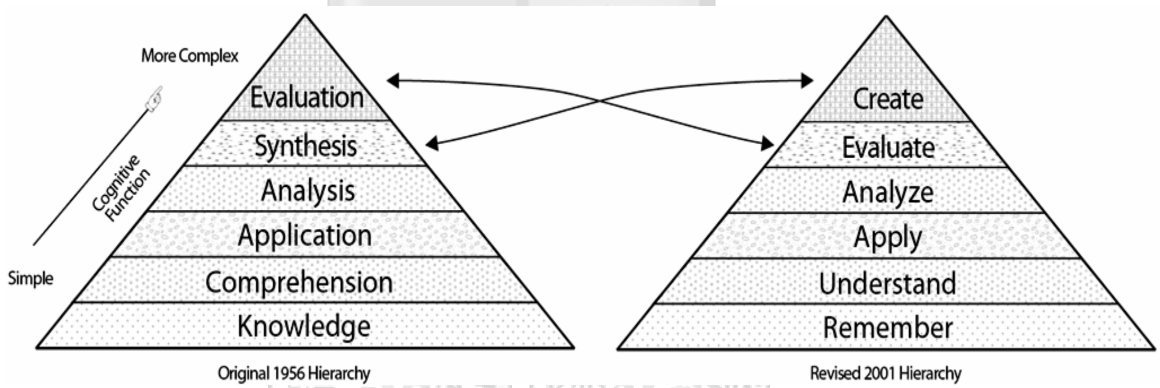


Figure 2.7: Revised Bloom Taxonomy (Anderson & Karthwohl, 2001)

There are six major categories, starting from simplest behavior to the most complex. The categories can be viewed as degrees of difficulties. That is, the first one must be mastered normally before the next one can take place. Figure 2.7 illustrates the Bloom Cognitive Taxonomy and which was revised by Anderson and Karthwohl (2001). The layers represent the levels of learning and each layer represents increasing complexity. Presented with each layer are sample verbs that describe actions or creations at that level of cognitive development.

Layer one is, "Remembering" where memory is used to produce definitions, facts charts, lists, or recitations. Layer two, "Understanding", includes producing drawings or summaries to demonstrate understanding. "Applying" is layer three, where concepts are applied to new situations through products like models, presentations, interviews or simulations." Analyzing" is layer four which includes "distinguishing" between the parts creating spreadsheets, surveys, charts, or diagrams. Critiques, recommendations, and reports are some of the products that can be created to demonstrate layer five which is "Evaluating". Creating, which is the sixth and top layer, puts the parts together in a new way.

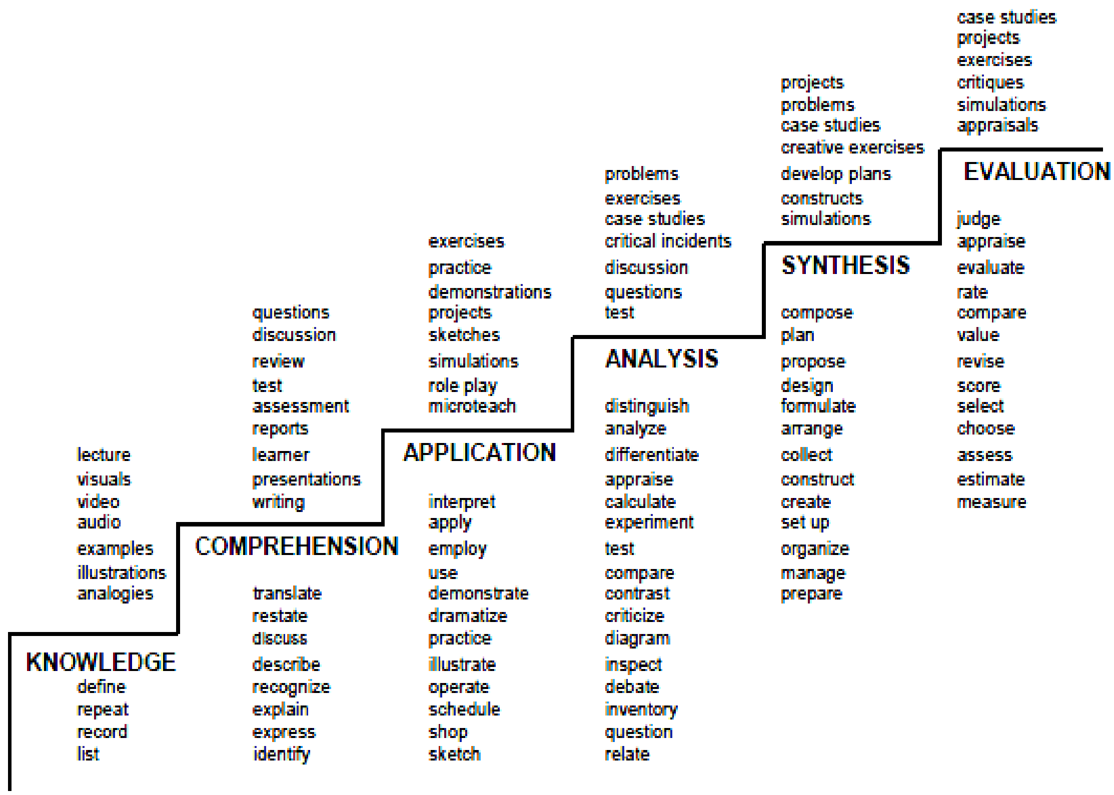


Figure 2.8: Bloom's Taxonomy Staircase (Source: Churches, 2008)

Figure 2.8 represents the cognitive levels in Bloom's original taxonomy, arranged in ascending order. On each step is a list of suggested activities for the specific level. Below each step is a list of verbs that are commonly used to create learning objectives. Benjamin Bloom never intended to generate instructional dogma but intended his work to be used in the assessment of expertise and to develop new ways in measuring what college students learned.

At present, this model becomes a basis in developing e-learning; transforming its contents, instructional delivery and assessment. His work contributed greatly in shifting the focus of educators to learning from teaching. Andrew Churches (2008) updated Bloom's work by introducing Bloom's Digital Taxonomy. The intention was to capture Bloom's cognitive levels to the 21st-century digital skills.

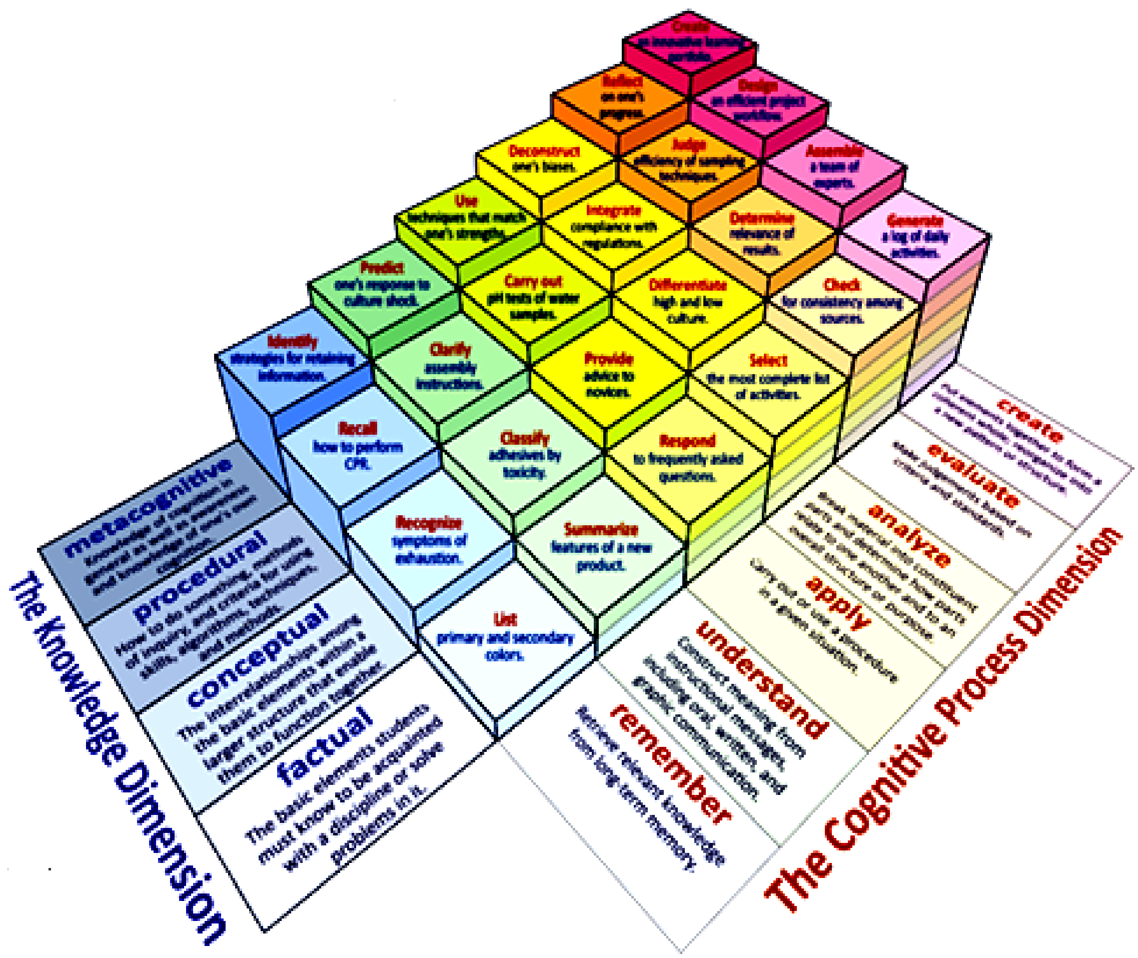


Figure 2.9: Taxonomy for Learning, Teaching, and Assessing: A Revision of Bloom's Taxonomy of Educational Objectives (Source: Anderson & Krathwol, 2001)

Figure 2.9 shows how the revised taxonomy arranges skills from the most basic to the most complex. The new version has two dimensions: the knowledge and cognitive processes and the sub-categories within each dimensions are more extensive and specific. The cognitive process dimension represents a continuum of increasing cognitive complexity - from remembering to creating while knowledge dimension represents a range from concrete (factual) to abstract (meta-cognitive).

2.5.1.3 Interactivity and Simulations

Many educators believe that interactive e-learning courseware which allows “learning by doing” arouses interest and generates motivation; this provides a more engaging experience for the learner. Interactivity is seen as part of a system where learners are not passive recipients of information, but they are engaged with a material that is responsive to their actions. Interactivity results in deeper learning because students can hypothesize to test their understanding, learn by mistakes and make sense of the unexpected and enhance knowledge and performance (Rosenberg 2000, p. 28).

An e-learning that merely allows the learner to navigate content or take a test is often labelled as interactive. This does not meet the criteria for meaningful interactivity outlined above. This is not similar to a design that provides simulation where a student can actively explore a simulated system or process (Thomas, 2001). Simulations and modelling tools are the best examples of complex, meaningful interactivity. Such applications model or represents a real or theoretical system, allowing users to manipulate input variables, change the system’s behavior and view the results. With such applications, learners can construct and test hypotheses and receive feedback as a result of their actions. Inclusion of interactive simulations in e-learning courses improves the quality and outcomes of e-learning. Simulations and visualization tools make it possible for students to bridge experience and abstraction which help to deepen understanding of ambiguous or challenging content. According to Clark and Craig (1992), interactivity is a factor that has the biggest impact on cognitive learning and is the most powerful model of instruction.

2.5.1.4 Multimedia Learning Effect

Studies have compared the effect of multimedia-based learning with traditional classroom-based learning. Allen (1998) discusses the effect of multimedia-based training. He claims that a good multimedia training is not only faster than classroom training, it is also better. People remember and retain longer in memory what they learn more accurately and use what they learn to improve their performance. Adams (1992) reviewed six studies that carefully compared multimedia training to classroom instruction: Learning gains were up to 56% greater while consistency of learning" (variance in learning across learners) was 50-60% better and content retention was 25-50% higher. Brett (1997) claims that multimedia-based learning is more motivating and exciting than the more traditional educational methods. It can also be claimed that using multimedia increases learning effectiveness and cognitive skills.

Clark and Craig (1992) present two assumptions that promote the use of multiple media. The first assumption is called additive assumption, or also called as instructional media. If used properly, this media can make valuable contributions to the learning and academic performance of students. Therefore, the instruction presented by several media increases learning benefits, because the benefit of each of the combined media are additive. The multiplicative assumption is that multimedia benefits are sometimes multiplicative, that is, greater than the sum of the benefits of individual media.

The use of multimedia such as graphics refer to variety of illustrations including line drawings, charts, photographs, motion graphics such as animation and video can indeed increase learning. Research shows that graphics improve learning through cognitive exercises, storing and retrieving ideas. Mayer (2003) found an average gain of 89% on transfer test from learner who studied lessons with text and graphics compared to learners whose lessons were limited to text alone. He also found that the integration of text near the visuals yielded an average improvement of 68%. Furthermore, explaining graphics with audios improve learning almost by 80%. According to Clark (2003), audio should be used in situations where overload is likely. For example, if a student is watching an animated demonstration of maybe five to six steps on how to use a software applications, the student needs to focus on his/her visual resources on the animation. If the student is reading the text and at the same time is watching the animation, then overload will likely to happen.

Learning is based on the engagement of the learner with the content of the instruction. According to Jones et al. (1997), in order to engage in learning, tasks need to be challenging, authentic, and multidisciplinary. Authentic in the sense that they correspond to the tasks in e-learning course and training and are seen useful for the future. Instruction actively engages the learner, and is generative. It involves experience and this makes the content more memorable than passive listening. Also, engaged learning fosters more holistic and creative solutions by using simulations, games, and workshops to experiment with new ideas. Moreover, engaged learning ignites commitment and motivates the participants closer to the goals.

2.5.2 Assessment

Assessment for learning is best described as a process by which assessment information is used by teachers and students to adjust their teaching strategies and learning strategies respectively. Assessment is a powerful process that can either optimise or inhibit learning, depending on how it is applied. This can be in a summative or formative form.

2.5.2.1 Summative Assessment

Summative assessment (“assessment of learning”) is generally done at the end of a course. In an educational setting, summative assessments are typically used to assign students a course grade, and by using a scaled grading system, enables the teacher to differentiate students. Both the teacher and the students need to be updated on the students’ abilities, progress, and overall development in the learning process. Summative assessment plays a critical role in this information gathering process. By conducting a variety of forms of summative assessment, the teacher will have a good understanding of where their students are in the learning process (Bilash, 2011). If the students have misconceptions or difficulty, it will redirect the student to perform corrective measures.

2.5.2.2 Formative Assessment

Formative assessment is a diagnostic testing procedures employed by teachers during the learning process. It provides information through qualitative feedback to modify teaching and learning activities to improve the student’s performance (Black & William, 2009). When properly incorporated in e-learning practice, it provides the needed information to adjust the teaching and learning while these are happening simultaneously. Adjustments help to ensure students to achieve targeted standard-based learning goals within a set time frame. According Cauley and McMillan (2010), formative assessment is one of the most powerful ways to enhance student motivation and achievements through practice, guidance, and feedback. Formative assessments determine the next steps during the learning process as the instruction approaches the summative assessment of student learning. Some of the instructional strategies that can be used formatively includes the following: criteria and goal setting, self-assessments, constructive feedback and student record keeping, and questioning strategies (Garrison & Ehringhaus, 2007).

i. *Criteria and goal setting* – Defining criteria and stating goals engage students in instruction and the learning process by creating clear expectations. In order to be successful, students need to understand and know the learning target/goal and the criteria of reaching it.

ii. *Self-assessment* – Student who can reflect while engaged in meta-cognitive thinking are involved in their learning. Students will be allowed to modify inputs or change variables in the simulations to be engaged with the learning process. They also assess the output by using the "learning by doing" approach and assess readiness of the *to* summative examinations.

iii. *Constructive feedback* – Students who receive positive feedback, guidance or help provide learners to continue the learning process. For example, feedback should be constructive so as not to hinder the learning process. It must also consider sensitivity since assessment has an emotional impact. It also recommend ways on how to improve the learning process.

iv. *Student record keeping* – helps student better understand their own learning as evidenced by their work and effort in their learning process. This process of students keeping ongoing records will not only engage students, it also helps them to see beyond "grade" and to evaluate where they started and the progress they are making toward the learning goal.

v. *Questioning Strategies* - The question type currently dominating large-scale computer-based testing and many e-learning assessments is in the standard multiple-choice question, which generally includes a prompt followed by a small set of responses from which students are expected to select the best choice. This kind of task can be scored easily by a variety of electronic means. It also offers some attractive features for assessing the format. However, if e-learning developers adapt this sole format as the focus in this emerging field of learning, then much of the computer platform's potential for rich and embedded assessment can be sacrificed. If the design of e-learning materials uses multimedia and interactivity to increase cognitive development, the same idea should also be adapted in creating assessment to guarantee mental skills and development.

In creating items in the assessment process, the development of questionnaires that guaranteed cognitive development and how it should be implemented was investigated. The classic work of Anderson (2001) adapted the concepts of Bloom's revised taxonomy and suggested questionnaires schema as shown in Table 2.4.a (lower hierarchy) and Table 2.4.b (higher hierarchy). This new taxonomy reflects a more active and accurate form of thinking (Pohl, 2000).

Table 2.4A: Bloom Questionnaire Schema

Category	Example and Key Words (verbs)	Level
Remembering: Recall previous learned information.	Examples: Recite a policy. Quote prices from memory to a customer. Knows the safety rules. Key Words: defines, describes, identifies, knows, labels, lists, matches, names, outlines, recalls, recognizes, reproduces, selects, states.	
Understanding: Comprehending the meaning, translation, interpolation, and interpretation of instructions and problems. State a problem in one's own words.	Examples: Rewrites the principles of test writing. Explain in one's own words the steps for performing a complex task. Translates an equation into a computer spreadsheet. Key Words: comprehends, converts, defends, distinguishes, estimates, explains, extends, generalizes, gives an example, infers, interprets, paraphrases, predicts, rewrites, summarizes, translates.	L O W E R
Applying: Use a concept in a new situation or unprompted use of an abstraction. Applies what was learned in the classroom into novel situations in the work place.	Examples: Use a manual to calculate an employee's vacation time. Apply laws of statistics to evaluate the reliability of a written test Key Words: applies, changes, computes, constructs, demonstrates, discovers, manipulates, modifies, operates, predicts, prepares, produces, relates, shows, solves, uses.	

There are many ways in which assessment items can be innovative and reinforce mental development when delivered by computer. The work of Parshall, Davey and Pashley (2000) studied one organizational scheme which describes the innovative features for computer-administered items, such as the technological enhancements of sound, graphics, animation, video or other new media incorporated into the item and the response. This work showed innovative formats where students can, for instance, click on graphics, drag or move objects, re-order a series of statements or pictures, or construct a graph or other representation. These innovations of assessment can hypothetically improve cognition and lead to higher academic outcomes.

Table 2.4B: Bloom Questionnaire Schema

Category	Example and Key Words (verbs)	Level
Analyzing: Separates material or concepts into component parts so that its organizational structure may be understood. Distinguishes between facts and inferences.	Examples: Troubleshoot a piece of equipment by using logical deduction. Recognize logical fallacies in reasoning. Gathers information from a department and selects the required tasks for training. Key Words: analyzes, breaks down, compares, contrasts, diagrams, deconstructs, differentiates, discriminates, distinguishes, identifies, illustrates, infers, outlines, relates, selects, separates.	HIGHER
Evaluating: Make judgments about the value of ideas or materials.	Examples: Select the most effective solution. Hire the most qualified candidate. Explain and justify a new budget. Key Words: appraises, compares, concludes, contrasts, criticizes, critiques, defends, describes, discriminates, evaluates, explains, interprets, justifies, relates, summarizes, supports.	
Creating: Builds a structure or pattern from diverse elements. Put parts together to form a whole, with emphasis on creating a new meaning or structure.	Examples: Write a company operations or process manual. Design a machine to perform a specific task. Integrates training from several sources to solve a problem. Revises and process to improve the outcome. Key Words: categorizes, combines, compiles, composes, creates, devises, designs, explains, generates, modifies, organizes, plans, rearranges, reconstructs, relates, reorganizes, revises, rewrites, summarizes, tells, writes.	

The work of Scalise and Wilson (2006) introduced a taxonomy or categorization of 28 innovative item types that may be useful in computer-based assessment. This is organized along the degree of constraint on the respondent's options for answering or interacting with the assessment item or task. Table 2.5 describes a set of iconic item types termed "intermediate constraint". The 28 example types are based on 7 categories of ordering, which involves successively decreasing response constraints from fully selected to fully constructed. Each category of constraint includes four iconic examples. References for the Taxonomy were drawn from a review of 44 papers and book chapters on item types and item designs – many of them well-established references regarding particular item types. They intend to consolidate considerations of item constraint for use in e-learning assessment designs. If such mechanism can be adapted in the assessment design, an additional impact in cognitive learning can definitely be obtained.

Table 2.5: Assessment Schema for E-learning (Scalise & Wilson, 2006)

***Most* Constrained** → ***Least* Constrained**

	Fully Selected	*Intermediate Constraint Item Types*					*Fully Constructed*
***Less* Complex**	**1. Multiple Choice**	**2. Selection/ Identification**	**3. Reordering/ Rearrangement**	**4. Substitution/ Correction**	**5. Completion**	**6. Construction**	**7. Presentation/ Portfolio**
	1A. *True/False* (Haladyna, 1994c, p.54)	2A. *Multiple True/False* (Haladyna, 1994c, p.58)	3A. *Matching* (Osterlind, 1998, p.234; Haladyna, 1994c, p.50)	4A. *Interlinear* (Haladyna, 1994c, p.65)	5A. *Single Numerical Constructed* (Parshall et al, 2002, p. 87)	6A. *Open-Ended Multiple Choice* (Haladyna, 1994c, p.49)	7A. *Project* (Bennett, 1993, p.4)
	1B. *Alternate Choice* (Haladyna, 1994c, p.53)	2B. *Yes/No with Explanation* (McDonald, 2002, p.110)	3B. *Categorizing* (Bennett, 1993, p.44)	4B. *Sore-Finger* (Haladyna, 1994c, p.67)	5B. *Short-Answer & Sentence Completion* (Osterlind, 1998, p.237)	6B. *Figural Constructed Response* (Parshall et al, 2002, p.87)	7B. *Demonstration, Experiment, Performance* (Bennett, 1993, p.45)
	1C. *Conventional or Standard Multiple Choice* (Haladyna, 1994c, p.47)	2C. *Multiple Answer* (Parshall et al, 2002, p.2; Haladyna, 1994c, p.60)	3C. *Ranking & Sequencing* (Parshall et al, 2002, p.2)	4C. *Limited Figural Drawing* (Bennett, 1993, p.44)	5C. *Cloze-Procedure* (Osterlind, 1998, p.242)	6C. *Concept Map* (Shavelson, R. J., 2001; Chung & Baker, 1997)	7C. *Discussion, Interview* (Bennett, 1993, p.45)
***More* Complex**	1D. *Multiple Choice with New Media Distractors* (Parshall et al, 2002, p.87)	2D. *Complex Multiple Choice* (Haladyna, 1994c, p.57)	3D. *Assembling Proof* (Bennett, 1993, p.44)	4D. *Bug/Fault Correction* (Bennett, 1993, p.44)	5D. *Matrix Completion* (Embretson, S, 2002, p. 225)	6D. *Essay* (Page et al, 1995, 561-565) & *Automated Editing* (Breland et al, 2001, pp.1-64)	7D. *Diagnosis, Teaching* (Bennett, 1993, p.4)

2.6 Synthesis of the Literature

The findings in the literature have proven that personalization and the creation of an individualized learning path is an important and timely issue for web-based learning and e-learning systems. Several studies have been established and the learning benefits of their proposed models have been emphasized. For personalization, several algorithms have been used in the area of artificial intelligence from simple to complex implementation. Simple algorithms used feedback and learning difficulty, learning preferences to personalization of learning, while complex used neural network, fuzzy logic, genetic algorithm, ant colony optimization and item response theory. These complex algorithms are very tedious and expensive in programming, implementation and maintenance. From these, several issues have emerged. For example, in genetic algorithms, the reliability of data samples (population – number of lessons) is considerably small while the ant colonization technique is quite complicated to implement. These complications include the use of rule-based prescriptive planning and the stochastic computation of the learner’s formerly traveled paths and performances. The use of artificial neural network on the other hand, needs to consider the interconnection pattern between layers, weights, activation function and others. In item response theory or ITR, a feedback mechanism is prompted to students to collect the response then modified the weight of the learning materials. The used of maximum likelihood estimation or MLE is used to estimate learners’ ability to provide individual learning path, but the used of collaborative voting approach to adjust the difficulty of learning materials is very tedious e.g. the number of learners currently online, and the time when voting will be conducted. In fuzzy logic, several variables such as learning styles, learning modalities, cognitive style and competencies is extracted to create a students’ knowledge model, prompting it difficult to implement in real word. With this gap, an alternative and a more reliable personalized and performance-based matrix and evolutionary technique such as selection algorithm and reinforcement learning can provide a more realistic personalized learning path and hypothetically produce better results and learning impact.

In the concepts of selection algorithms, three techniques have been evaluated. These are the roulette wheel selection algorithm, truncation selection, and tournament selection algorithms. Among these three selections, it was noted that the roulette wheel selection algorithm (RWSA) is the most suitable due to number of population available. Normally, the population to be manipulated for recombination should be hundreds to thousands but RWSA is capable for small population. The RWSA provides zero bias since it can easily manipulated by improving the implementation of the algorithm. Applying sorting and linear ranking provide uniform scaling. The fitness value is dynamic and it can be easily manipulated using performance matrix. The used of performance matrix is not applicable with truncation due to its bias and selection mechanism wherein a certain percentage of the population is directly eliminated. Given a 50% cut-off fitness value, all topics in the curriculum that will receive lower than 50 is subject for retention and needs corrective measures. Choosing 90% as cut-off value is likely impossible since students taking the course for the first time will not get this mark easily except for the highly motivated and fast learner. The tournament selection on the other hand, is very expensive to implement due to its repetitive and varying noise level and noise fitness level.

One noteworthy observation gathered from the literature is that although personalization of learning path was generated, majority of these researches did not identify stopped criterion and without identifying or attempt to correct learning difficulty. Upon identifying the misconceptions or learning difficulty, a mastery learning and reinforcement mechanism is employed to guarantee that learning process will occur. To guarantee that the learning process will take place, several factors affecting e-learning design which focuses on cognitive development domain were investigated. It is the most important learning domain and it is widely believed that the other domains will be likely developed from the cognitive domain. To support cognitive development, several learning theories and their implications as well as the instructional design and development of e-learning materials have been investigated ranging from content, instructional media and assessment. According to the above findings, the use of interactivity and simulation entice learning while engagement through different media and "learning-by-doing" provide better understanding and cognitive development. Moreover, the design of assessment module together with items/questionnaires adapted from the revised Bloom's Cognitive schema (Anderson, 2000) and the framework on e-learning assessment by Scalise and Wilson (2006) is used to guarantee that questions stored in database for practice examinations, end-chapter examinations and formative examinations will lead to quantifiable cognitive learning gain.

It can be concluded then that by integrating the roulette wheel selection algorithm (RWSA), mastery learning (ML) and reinforcement learning (RL) to produce personalized learning path, it remediated learning difficulty, enhanced and improved the learning process.

2.7 Conceptual Framework of the Study

The general conceptual framework of the study is to combine the existing relevant related literature to improve the e-learning system implementation in multi-faceted ways. Various considerations have been implemented in the development of study to be able to personalize learning sequence, perform mastery, reinforce learning, and create a working prototype. In this section, different components of the e-learning prototype have been discussed. Also, the system flow and architecture of how a roulette wheel selection as revolutionary algorithm to personalize learning sequence, perform mastery and then reinforcement learning is recommended.

2.7.1 System Components

There are four major components incorporated in the system. These are content and assessment, personalization process, reinforcement, and mastery learning. Figure 2.10 shows these components.

First, personalization refers to the processes that involves recommendation of a most and individually suitable learning sequence for each students. In this component, the system collects different real time performances such as examination, study and review score of students. Formulas are used in order to derive a single numerical value called fitness value. This value is discussed in detail in Chapter 4 as the basis of Reverse Roulette Wheel Selection algorithms. Students that undergo reading the system will experience different kinds of personalization process such as personalized formative examinations, personalized reviewing and access to the explanation facilities and personalized summative examination.

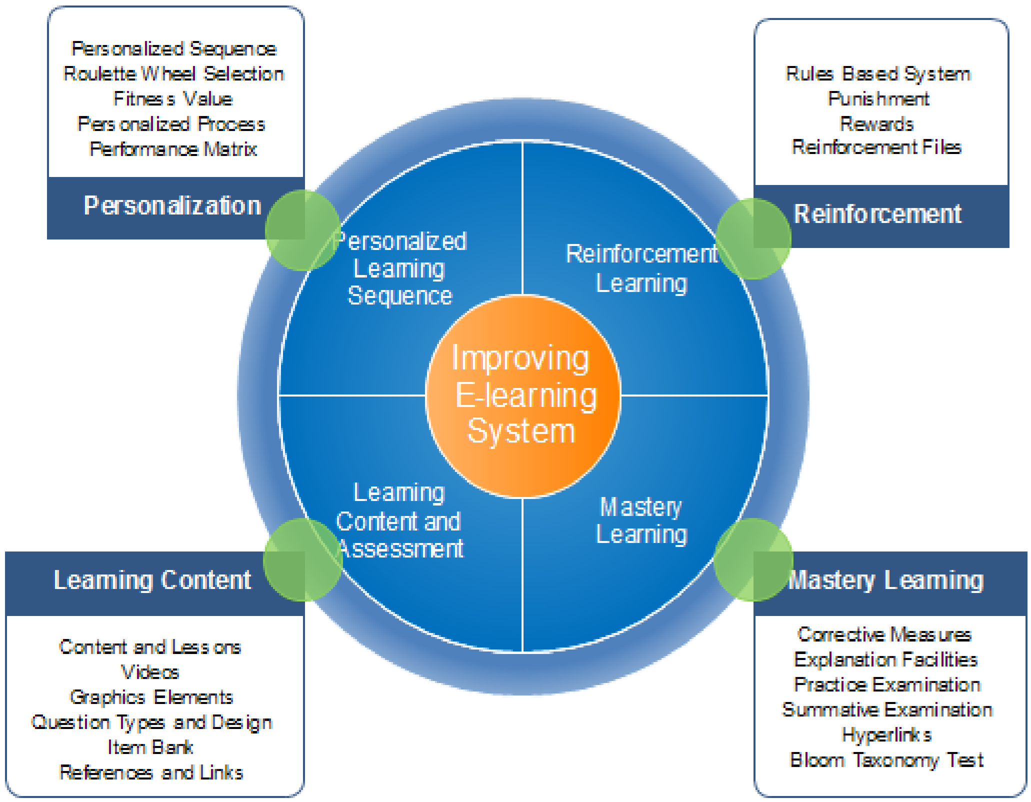


Figure 2.10: Components of the E-learning System

Second, learning content and assessment includes the design of item bank in the database and the development of questionnaires to be used in different examinations or assessments. In addition, it also involves the development of lessons and instructional materials presented in different media formats. Links and additional references for further reading are also included in this part of the system. Third, mastery learning involves different correctives measures, explanation facilities, practice or formative examination, random summative examination, and hyperlinks of related topics. Also in this section is the discussion and development of Bloom Taxonomy's as a measure of cognitive gain. Fourth is the reinforcement process which is responsible in giving cumulative rewards to the students and the implementation of giving punishments governed by set of rules. These set of rules is fired depending on the fitness value *fv*, of each lesson that determines a number of files to be reinforced to students.

2.7.2 Stop Criterion

At the end of the course, all students will undergo summative examination to determine their competency level. Initially, a 60-item examination is randomly generated by the system for each student, extracted from the item bank with different question types. No two-students can have the same set of questions, making the examination personalized. The number of questions selected for each lesson is proportional to the students' time in reading the learning materials. There are 12 lessons in the module to be learned.

Figure 2.11 shows how system flow works during implementation. The system in the first generation creates a random summative examination to populate the students' performance table. If the students obtain an overall average of 75, then they pass the initial competency level or, then they pass the course. However, if the student fails the first summative examination, a single numerical fitness value will be computed by extracting the different performance indicators from the students' profile. The results will be fed into reversed RWSA to recommend a personalized learning sequence. Then the student will undergo mastery and reinforcement process. Upon completion of the mastery and reinforcement learning, the student will undergo a second summative examination. Questions are derived based on the recent recommended personalized learning sequence. The system will compute the cumulative rewards and added to the summative examination results. If the student passes, the system will record his/her new numerical competency equivalent. However, in the event that the sum of cumulative rewards and summative examination results is not sufficient, recent personalized learning sequence will compute again the fitness value and then subject for mastery and reinforcement. This process can be repeated up to the third generation.

The personalized learning sequence has been recommended based on the collected data during the learning process and the results of the summative examination. This makes the individual profiling of students possible. The proposed learning path can simultaneously consider the curriculum difficulty level and the curriculum continuity of the next curriculum while implementing the personalized learning sequence in the learning process. During reinforcement, a numerical reward is given if the students satisfactorily perform corrective activities. On the other hand, a student who does not satisfactorily perform these corrective activities is given reading materials as a form of punishment based on the punishment-rules system. The students will undergo mastery learning in the form of randomly selected formative examination to practice their comprehension or understanding of the previously learned lesson before taking the summative examination to identify their new competency level.

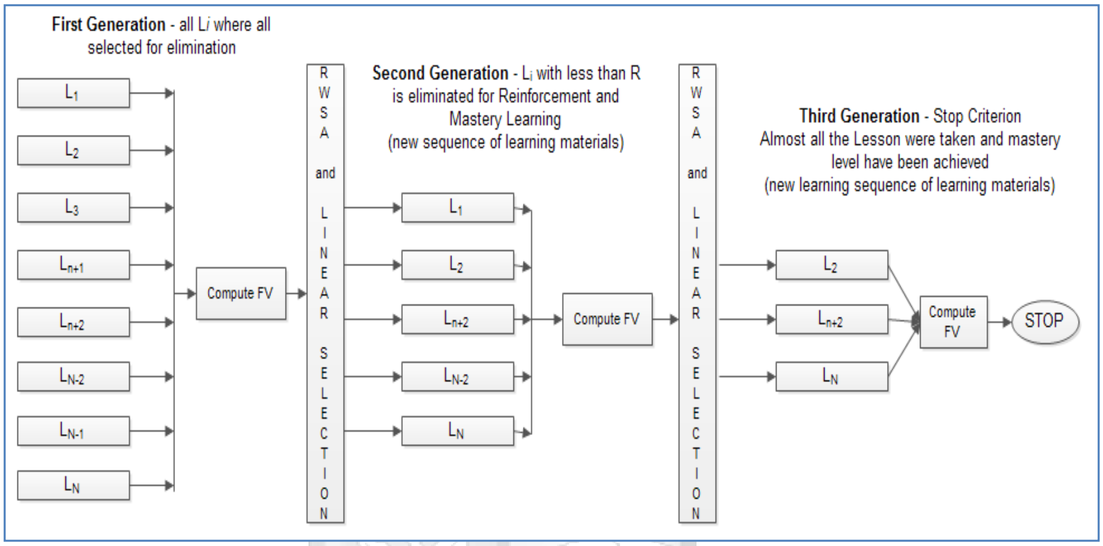


Figure 2.11: PLS Generation and Stop Criterion

2.7.3 System Architecture

A general system architecture of the study is presented in Figure 2.12. By default the students will undergo reading and training the e-learning course materials and it is assumed that all students have equal leveling stage.

Topics will be presented in a sequential manner; this is like reading an online book or manual that supports incremental learning process. At the end of each chapter, a practice examination (formative) module is provided, which allows students to review current topics and assess their individual performance. After the prescribed weeks or when they finish their training module, students will undergo a summative computer examination. Afterwards, it will be determined if the students are ready to learn new learning materials or can pass the course. If students receive the passing mark of 75 or higher, then they can proceed to the next learning material or the next course. If students fail*s* the summative examination, they need to repeat the course and start the personalization process by employing the reversed roulette wheel selection algorithm and then the mastery and reinforcement learning. But first, the historical data of the students will be reloaded by activating their previous performances such as results, study and review statistics to produce the function value *fv*. Based on *fv*, the RWSA will eliminate topics higher than random number *r* that are generated by the computer, and will retain topics perceived to have not been mastered and which are needed to be re-learned by the student. Topics that received low *fv* will remain and will undergo recombination and will be arranged into descending order based on the number of reinforcement process determined by reinforcement rules. The lower the reinforcement process, the more likely it will be prioritized in the recombination process, thereby creating a personalized learning sequence (PLS). Each list from the PLS will undergo corrective and enrichment activities at reinforcement learning (RL) module.

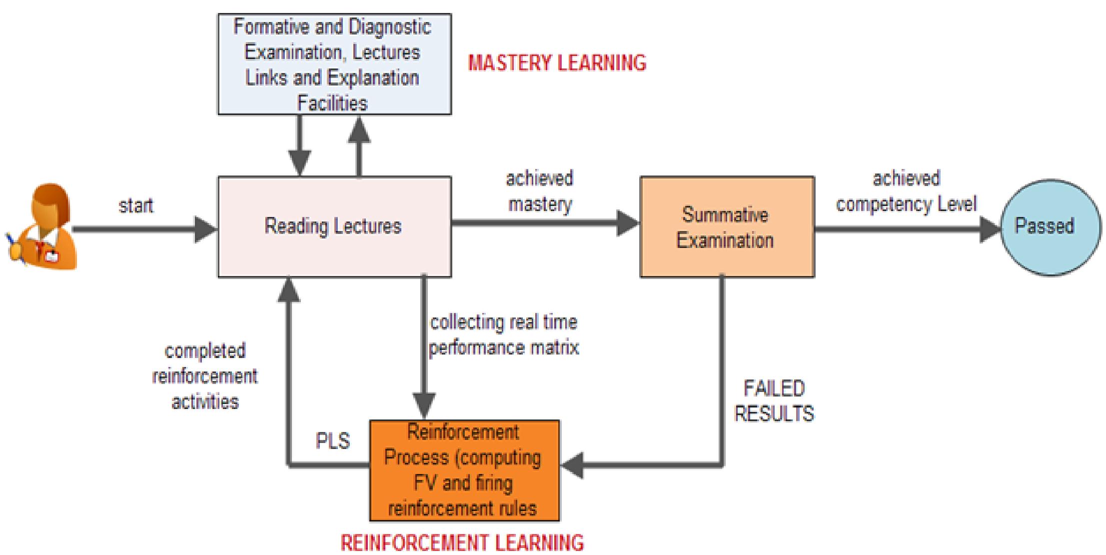


Figure 2.12: System Architecture of RWSA - RL in E-learning System

In RL, the PLS needs to be re-learned using different materials such as related lessons, videos and other situational exercises as punishment while correcting the learning difficulty. When learners complete their corrective activities and the reinforcement process, they are administered with a summative assessment or remedial examination. This covers the same concepts and learning goals but is not composed of exactly the same problems or questions. This is to ensure that learners can learn the important concepts rather than simply memorize the answers to specific questions. If they fail to reach the mastery level, the system will recommend a reinforcement (punishment). Otherwise, they are perceived to be ready and can therefore proceed to the next learning materials or to the next course.

Chapter 3: Research Design and Methodology

Do not repeat the tactics which have gained you one
victory, but let your methods be regulated
by the infinite variety of circumstances.
Sun Tzu (490 BC)

Perception is strong and sight is weak. In strategy
it is important to see distant things as if they were
close and to take distanced view of close things.
Miyamoto Musashi (1584 - 1645)

Imagination is the highest form of research.
Albert Einstein (1879 - 1955)

3.1 Introduction

The review of literature has shown recurring themes which emphasized the importance of personalized learning path in e-learning implementation (QIA-UK, 2008; USD. of Education, 2009; UNESCO, 2012). Currently, several approaches which support the improvement of personalized learning have been proposed and studied. Revolutionary techniques and strategies to expand the scope of this system and to improve the learning process have been developed. This chapter discusses the methodologies and strategies used in the design of the e-learning prototype and how the various mechanisms presented in the conceptual framework were implemented.

3.2 Case Study: Sirte University

Sirte University, which is formerly known as Al-Tahadi University is a public university in the heart of rich oiled country, Libya. It has campuses in Benjawad, Hun, Juffra and Zamzam, and satellite schools. It caters for 10,000 students from all walks of life. It was established in 1991 and was originally under the umbrella of Bengazi University. In 1993, the university was granted independence due to its population and massive economic expansion of the city. The university became the center of economic activity until war erupted in 2011. To date, there are 14 faculties with numerous departments.

3.2.1 Rationale and Motivation of the Study

Failures of the many students in the university can be attributed to non-completion of requirements, failures in examinations, incomplete trainings, excessive absences, insufficient skills and other reasons. The average failing mark for the last three semester ranges from 30 to 70 percent (Menem, 2013). This is a big number of students who need attention. In effect, there is a low turnout of graduates because the average years a student graduates from the university is 6.5 for a 4-year course. Also, the average age the students graduate is 24 as compared to the US, Africa and Asia which is 22-23 and 19-21 years old respectively. (The New York Times, 2012; McClain, 2013, UNESCO, 2006). Recent events like the war in Libya further deteriorate academic competency as evident of the high absenteeism of students due to restricted mobility and threat to security and safety. According to the composition of current university population, the male to female ratio is 1:8, making the majority of population female. Among the female students, 90 percent is of marrying age and they are therefore, basically busy with family commitments and have no time to attend formal classes.

In 2013, Sirte University reluctantly released 24M Libyan dinars (18.5 million dollars) to pay students to attend the university. A student who wanted to enroll was given 1,850 dollars per year. This is considered to be a wasted additional cost for government. In early as 2010, the Libyan Ministry of Education envisioned and initiated the "IT Infrastructure and Education for 2020". This is a program to integrate ICT infrastructure into education and remediate the unnecessary cost of spending and to lessen the number of years the students stay at the university. In the succeeding years, the Libyan government spearheaded the adaption of e-learning education as solution to the problem. This effort is evident by the research output in the field of e-learning. The work of Ballera and Musa (2011) created an e-learning prototype that deals with the two level of personalizing learning sequence using genetic algorithms and learning style but the model was difficult to manage and implement due the complexity of programming and lack of collected prior knowledge. Various suggestions and prototyping such as the incorporation of artificial agent that play multiple roles (Ballera, Elssaedi & Zhody, 2013), to help the students in learning process, employment of social agent to interject feedback (Ballera & Aziza, 2012), development of a content-based and interactive e-learning system using the ADDIE learning model (Ballera & Elssaedi, 2013) and the recently proposed use of case-based reasoning approach have been tested (Ballera, Lukandu, & Radwan, 2013). These studies require algorithmic process and are technically difficult to maintain.

Failure of students in a university setting does not totally indicate failure of understanding. Students fail due to minimal performance indicators. For example, when a student obtains a failing mark at the end of the semester wherein 12 examinations were given, there are students who did not fail in all the examinations but rather, their grades were pulled down by the dismal results of other examinations. In view of this, two basic questions must be answered: “Should students be encouraged to repeatedly read the module if they fail the course/s?”and “Should learners be allowed to spend their time reading all the modules instead of learning from more productive learning materials?”. Normally, educational strategists are given three weeks to prepare and compute the final grades of students and have enough time to remediate the learning difficulty of students. Educational developers and strategists should include immediate and post remediation process that will allow students to skip modules that they have already learned and passed. This is an issue that needs further attention, especially when it comes to e-learning based instruction. Learners should be given an opportunity to study and take the examination again provided they undergo remediation process.

3.2.2 Study Design and Protocol

The study is organized within the context of Design and Analysis of Algorithms class which is taught at Sirte University, Libya. The entire data collection and training have a duration of 18 weeks or one semester. All students are familiar with the use of electronic materials and have seen the implementation of the e-learning system and were given one week familiarization of the system flow and navigation. During the training, students were given examinations which were administered every three weeks to determine their knowledge level of the course.

Initially, the student were given the same module which would level the stage. At the leveling stage, the lessons were sequentially presented to establish the students' prior knowledge of the course and to start building their respective performance history matrices. To pass the course, the students were required to complete several assessment tasks during the study period, take a final examination and must have a minimum overall aggregate score of 75. If the student fails, a recommended re-study module will be given.

Prior to implementation, students were informed about the research and the task involved. Students had time to navigate the e-learning system to familiarize and be directly involved in the learning process. Participation in the study was strictly voluntary and students who chose not to participate were permitted to work on course assignments and course handouts/lectures. Also, students were discouraged not to take down notes and directed to pay attention to the lesson at hand, but the students could review lessons in the course module several times. If some issues arouse during the learning process, the researcher provided necessary assistance in support for blended learning. At the end of the lesson, participants were directed to practice the module (formative assessment).

3.3 Population and Sampling

Forty-one (41) students who were enrolled participated in the experimental study. A special arrangement or permission was granted by the Head and the Dean of the Department of Computer Science so that students can participate in the said study. Out of the selected 41 students, 6 males and 35 females voluntarily opted to use the e-learning course. The students are third and fourth year undergraduate students.

Direct observations of every individual in the population cannot be made by the researchers. Instead, data from a subset of individuals – a sample – were collected and observations were made to make inferences about the entire population. Ideally, the sample corresponds to the larger population on the characteristic(s) of interest. In this case, the researcher's conclusions from the sample are applicable to the entire population. In establishing the overall acceptability of the software and critical even recall, a survey with purposive sampling was used. All students in the study participated in the survey.

Non-probability sampling was used to survey the computing software acceptability and internal consistency of the software and questionnaires among professional staff. The composition of the professional staff is as follows: four in the managerial level (all PhD holders), six teaching staff (three PhD holders and three Masters degree holders) and two staff members from the University Technical Department which maintain the University portal. Population elements were selected on the basis of their availability or because of the researcher's personal judgment that they were representative of the entire population. One of the most common types of non-probability sample is called a convenience sample – not because such samples are necessarily easy to recruit, but because these individuals are readily available and therefore there is no need to select from the entire population.

3.4 Research Design

The central role of research design is to minimize the chance of drawing incorrect causal inferences from data. Design is a logical task undertaken to ensure that questions can be answered by the evidence collected or to test theories as clearly as possible. In this study, both descriptive and experimental designs were used.

3.4.1 Descriptive Design

This design also provides rich descriptive details about people, objects, and other phenomena. It often involves extensive observation and note-taking, as well as in-depth narrative. It does not lend itself to in-depth analysis or hypothesis testing. However, a descriptive research design can serve as a first step to identify important factors and laying a foundation for a more rigorous research.

3.4.1.1 Learning Content

The content of the e-learning materials has been used and is the product of five-year teaching. This has also been improved for the purpose of creating an e-learning prototype. There are 12 lessons with 65 subsections. The course contents were specifically designed for the students. Their backgrounds and communication problems were considered, making the content more focused in problem solving and application types of discussion. Aside from the lessons and discussion of the subsections, twenty four (24) interactive MHTML files, seven (7) embedded videos, fourteen (14) simulations, twenty two (22) PowerPoint, forty five (45) PDF files, twenty two (22) words files, sixteen (16) executable files, sixteen (16) source codes and two (2) excel files were used. Figure 3.1 shows the components of the learning design. The overall design of the learning materials follows the concepts and implementation on the work of Ballera and Elssaedi (2013). Different principles were used in e-learning development such as the principles of using audios, sounds, and text presentation as discussed by Mayer and Clark (2003). This study made use of the modified Bloom cognitive taxonomy by Churches (2008).

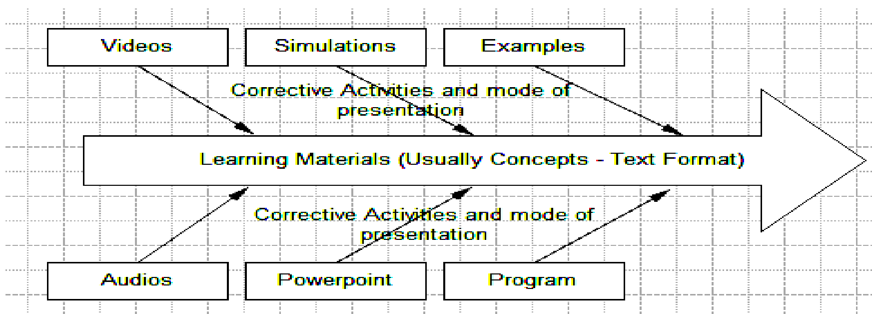


Figure 3.1: Component of Learning Materials

3.4.1.2 Syllabus

The syllabus content was approved by the University Quality Assurance Office (QA). Likewise, the content was approved by the Syllabus Committee of the Department of Computer Science. The original passing competency level is 50, but this was changed to 75 in consonance with the certification competency (CISCO, 2012). Activities and deliverables both for blended learning and online are specifically stipulated in the syllabus.

3.4.1.3 Item Bank and Assessment Design

The item bank is a repository of different question types with varying difficulty level. It contains 280 questions with explanation facilities divided among twelve (12) question types and are used to produce the Bloom Cognitive Taxonomy examination, the random formative examination, and the random summative examination. Questions were formulated and designed using the Bloom Cognitive Taxonomy Schema. The following were the designed question types stored in the Item Bank database: Complex Single Multiple Choice Questions (CSMA), Fill-in the Blanks and Enumeration Questions (FIBE), Matching and Categorization Questions (MTCQ), Matrix Completion Questions (MCOQ), Multiple Alternative Questions (MALT), Multiple Choice with Illustrative Diagrams (MCID), Multiple Choice and Multiple Answer Questions (MCMA), Multiple True or False Questions (MATF), Single Answer Multiple Choice Questions (SAMC), Single Numerical Construction Question(SNCQ), Situational Multiple Choice Question (SMCQ), and True or False Questions (TOFQ).

3.4.2 Experimental Design

Experimental designs are often touted as the most "rigorous" of all research designs or, as the "gold standard" which all other designs are judged. Experiment is the strongest design with respect to internal validity. In this study, it determines whether the prototype was able to personalize the learning sequence, and implement mastery and reinforcement learning which hypothetically could lead to higher learning benefits. To validate and answer the research questions, an e-learning prototype was developed and implemented which was capable of producing conclusive data about the Bloom Cognitive Taxonomy, dynamically populate performance matrices for student profiles, capable of recommending personalized learning sequence, and perform mastery and reinforcements. To recommend a personalized learning sequence, several formulas have been developed to formulate the fitness function. These formulas were developed and incorporated to the e-learning system.

3.4.2.1 Bloom Cognitive Taxonomy

The Bloom Cognitive Taxonomy measures the cognitive performance of the students. Sixty questions for Bloom was created using the Bloom Taxonomy Schema found in Appendix C. These questions are readily available in the Item Bank in the database. The examinations were divided into six categories to facilitate six phases of Bloom Taxonomy and were taken four times throughout the study. The examination is activated to measure the improvement of students as the training neared its end. The e-learning prototype shows the graphs of both individual and overall class average performance.

3.4.2.2 Performance Matrix

The e-learning prototype populated dynamically different tables in the database as students do their learning process. Three performances indicator were collected: examinations performance, review performance, and study performance. The following are the brief descriptions of the three performance indicators:

i. *Examination Performance* - The results are the direct information about the student's knowledge. The performance is dynamically constructed based on the student's background in reading the learning materials. The questions are provided to cover the topics, which are most recently completed. Each question has a certain level of difficulty. When one answers a harder question correctly, it demonstrates the person's higher ability than correctly answering an easier question.

ii. *Study Performance* - Study performance refers to the main interaction that the students have with the learning environment through viewing or listening to the course materials in multimedia forms. The study performance is used to judge how much comprehension the student has gained through these learning activities.

iii. *Review Performance* - The *review topics performance* score on a topic shows the records of how much the student has repeatedly viewed the content to review the topic (clicking arrow back and forth). It is based on how many times the topic is reviewed and how much of the materials are viewed each time.

3.4.2.3 Personalized Learning Sequence

The system adopted and improved the algorithm of Roulette Wheel Selection to recommend personalized learning sequence or PLS. The software dynamically recommended PLS mechanism individually among students by extracting their different performance matrices to produce a single numerical equivalent also known as the fitness value.

3.4.2.4 Reinforcement Metrics

Based on the recommended personalized learning sequence, the system dynamically activated and recommended the reinforcement process of students. The system suggested a number of files or activities based on the reinforcement rules fired in the system. The lower the fitness value was, the more files were activated. Reinforcement files were presented in various media formats. There were 60 rules coded in the program, with 78 reinforcement files.

3.4.2.5 Examination

Aside from the Bloom Cognitive diagnostic examination, two examinations were given namely the formative or practice and summative or final. During the formative examination, the system imposed several controlling mechanisms to guarantee learning of the materials, while the summative examination varied according to the time spent by the students in reading the materials. No two students could have the same set of questions. The summative examination varied according to the level of reinforcements. The higher the reinforcement, the smaller the number of questions was generated for the summative examination. The Bloom Taxonomy is a sixty item (60) question, equally divided among six categories. Initially, the summative examination is composed of sixty items, proportional to the time allotted in reading the materials then varies accordingly as the reinforcement process increased.

3.5 Data Collection Methods

In this study, primary data were collected in two ways. The first is the experimental collection where various tables were populated dynamically, manipulated, and extracted to generate several reports. Examination results, graphs, frequency of the practice, and personalization process were recorded in the system. The second was the survey which collected before and after the training. Two surveys were conducted in the study. The first survey was used to collect the evaluation of the features and functionality of the system and its internal consistency by the academic staff and IT professional. The survey was conducted prior to implementation to reflect on the students views, comments or suggestions. The second survey was used to collect demography, overall acceptability in terms of e-learning prototype's features and functionality, and theme extraction of students who experienced and used the system. The data were collected after the training. All the questions in the survey were checked and revised accordingly.

According to Kumar (2013), surveys are concerned with describing, analyzing, recording, and interpreting conditions that exist or existed. Surveys are only concerned with conditions or relationships that exist, opinions that are held, processes that are going on, effects that are evident or trends that are developing. They are primarily concerned with present but at times do consider past events and influences as they relate to current conditions.

3.6 Statistical Treatment and Theme Analysis

To determine the learning benefits and outcomes of the study, several statistical treatment and data analysis were employed.

3.6.1 Z-Test

A z-test is a statistical test used to determine whether two population means are different when the variances are known and the sample size is large. The reason the *z*-test works is that the sum of normally distributed random variables is also normally distributed. Z-tests are performed in cases where the underlying population is not normal and if *n* is large (above 30) and the population variance is known (Messy & Miller, 2013).

Equation 3.1: Population Variance is the formula in computing the sample variance where x_i corresponds to each observation in the sample, and $\bar{x}$ the mean of the sample.

$$s^2 = \frac{\sum_{i=1}^{n}(x_i - \bar{x})^2}{n-1} \quad \textbf{(3.1)}$$

Equation 3.2: Z-Test**,** is used to test a hypothesis with given significance level α, the critical value of z is calculated and checked whether it is in the critical region. Most often, the tests involve α = *:*05.

$$z = \frac{x - \mu}{s^2 / \sqrt{n}} \qquad \textbf{(3.2)}$$

During the survey, reliability and acceptability (staff survey) of the system were using Likert Scale of 1 to 5 while the same formula (Equation 3.2) was used to evaluate features and functionality of the students (Trochim, 2006). To test if the results were statistically significant the following hypotheses were:

H_1: $\mu < 4$ (student average agree with the system features)
H_0: $\mu \geq 4$ (student average does not agree with the system)

In one tailed, the null hypothesis is rejected if $z \geq z_\alpha$ (if the hypothesis is right-handed) or if $z \leq z_\alpha$ (if the hypothesis is left-handed). The most common z-values use is $z_{:05} = 1{:}645$. The hypothesis μ=4 was tested whether all respondents agree with the features, functionality, level of acceptability and reliability of the system according to the Likert scale.

3.6.2 Cronbach's Alpha

Cronbach's alpha provides a useful lower bound on reliability and measures internal consistency. It generally increases when the correlations between the items increase. Alpha coefficient measures the internal consistency of the system. Its maximum value is 1, and usually its minimum value is 0. A commonly-accepted rule of thumb is that an alpha of 0.6 indicates acceptable reliability and 0.7 or higher indicates good reliability. (George & Mallery, 2003; Vehkalahti, Puntanen & Tarkhonen, 2006; Tavakol & Dennick, 2011).

Equation 3.3: Crobach's Alpha is used to measure the internal consistency and acceptability of all the system questionnaires stored in the Item Bank, the content and features of the e-learning prototype. In particular, it was used for testing with a score between 0 and 1. The formula is given by Equation 3.3.

$$\alpha = \frac{k}{k-1}\left(1-\frac{\sum_{j=1}^{k}\mathrm{var}(x_j)}{\mathrm{var}(x_0)}\right) \qquad \textbf{(3.3)}$$

3.6.3 Theme Analysis: Sentiment and Theme Extraction

To correlate the results of the Bloom's cognitive examination, theme extraction using a special software called Semantria was used to analyze the digital transcripts of the students. The students were requested to write a report in one or two sentences about their experiences and perceptions in using the system and the new learning delivery. In particular, the respondents did the following: gave simple summary of actions they had done as part of their participation, proposed and discussed some strategies that could be applied in a situation, stated the topics for which they got assistance, examples and topics that were products of their work, and finally provided their personal reflection and experiences in participating in the exploratory study.

Semantria software extracts themes using the digital transcript of the students taken from the survey to determine and follow trends that appear over a period of time. Themes are noun phrases extracted from text and are the primary means of identifying the main ideas within the digital transcript. In addition, Semantria assigns a sentiment score to each extracted theme to understand the tone behind the themes.

After the digital transcript was sent to Semantria, the engine identified the basic parts of speech called POS tags. Figure 3.2 demonstrates how two simultaneous steps occur:

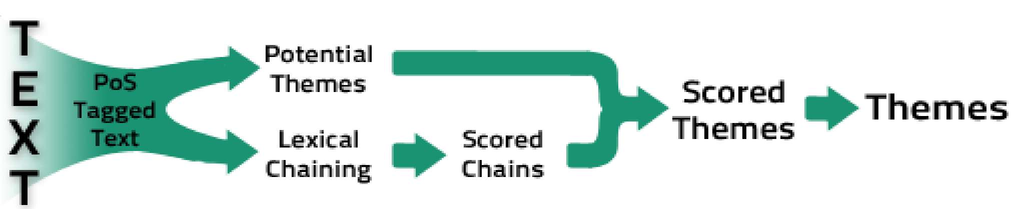


Figure 3.2: Theme Extraction (Semantria, 2014)

i. Potential themes are extracted from POS tags and kept for scoring. A process called Lexical Chaining occurs, which involves linking sentences through nouns that are synonyms or otherwise related to each other. In this way, Semantria is able to establish a conceptual chain in the content.

ii. Once the Lexical Chaining and Potential Theme Extraction steps are finished, each theme is scored based on Semantria's algorithms. Potential themes that belong to the highest Lexical Chain are assigned the highest score. The algorithm also takes context and noun-phrase placement into account when scoring themes. If there are fewer than four chains in the given text, the algorithm reverts to scoring purely based on count.

3.7 Recommended Environment

To meet the recommended system requirements, for the features and functionalities of the e-learning prototype, the system requires an active Internet connection using MyDSL, Rifi or via Wi-Fi using WiMax. Cellular internet browsing test was not yet conducted. The following were the minimum requirements:

3.7.1 XAMPP

XAMPP is a free package of web services developed by Apache Friends. The package is cross-platform, so it can work in Windows, Mac OS X, Solaris and Linux. It was originally designed as a development application, so that people could test their scripts, codes and websites on their own computers without the need of an external server using all the services needed. The package supports and include the following:

+ Apache 2.2.11

+ MySQL 5.1.33 (Community Server)

+ PHP 5.2.9 + PEAR (Support for PHP 4 has been discontinued)

+ XAMPP Control Version 2.5 from www.nat32.com

+ XAMPP CLI Bundle 1.3 from Carsten Wiedmann

+ XAMPP Security 1.0

+ SQLite 2.8.15

+ OpenSSL 0.9.8i

+ phpMyAdmin 3.1.3.1

+ ADOdb 5.06a

+ Mercury Mail Transport System v4.62

+ FileZilla FTP Server 0.9.31

+ Webalizer 2.01-10

+ Zend Optimizer 3.3.0

+ eAccelerator 0.9.5.3 für PHP 5.2.9 (but not activated in the php.ini)

3.7.2 Personal Computer

+Microsoft Windows 7 or later

+Google Chrome 28

+64 bit Operating System

3.7.3 Redactor

Redactor is powerful, flexible, and easy to use tool. It provides great service without the clients spending expensive time on complex customization. Most features work out of the box (library package) and are customizable with literally a line of code. This was used primarily in the design of assessments that cater 12 question types. It customized the toolbars, used to drag and drop the images needed for the assessments, and linking explanation facilities to specific lessons.

3.8 Summary

In this chapter, the research methodology of the study was outlined both qualitative and quantitative approaches of data collection were briefly discussed. Experimental research design was applied to show the e-learning capability and to implement the reverse roulette wheel selection algorithm and reinforcement learning. Data were dynamically collected, populated, and extracted in different tables of the databases. Data were analyzed using a special software for theme extraction and sentiment analysis. Moreover, the study employed statistical treatment to validate the data and measure the internal consistency of the content and the questionnaires stored in the Item Bank database.

Chapter 4: Modeling the Fitness Function and Reinforcement Process

Unless a variety of opinions are laid before us, we have no opportunity of selection, but are bound of necessity to adopt the particular view which may have been brought forward.

Herodutus (5 BC)

Take time to deliberate, but when the time for action comes, stop thinking and go in.

Napoleon Bonaparte (1769 – 1821)

Research is to see what everybody else has seen, and to think that nobody else has thought.

Albert Szent Gyorgyi (Nobel Peace Prize, 1893-1986)

4.1 Introduction

This chapter presents the improved implementation of Roulette Wheel Selection algorithm (RSWA) and its capability to heuristically produce a personalized learning sequence from e-learning curriculum vector. This further discusses the development of mathematical analysis and notations used throughout the study. These mathematical notations are used to arrive at a single numerical value called fitness assignment or fitness function, *fv*, a necessary variable to perform selections and recombination in the learning process. Throughout the study, the term "individual" or "chromosome" refers to the lesson in the curriculum vector. The latter part of this chapter provides understanding of the reinforcement process in machine learning of artificial intelligence and the concepts of mastery learning notable in self-paced education environment. These concepts combined and paved for the new development of educational strategy to improve the learning process of students in e-learning teaching environment.

4.2 Reversed Roulette Wheel Selection

The Roulette Wheel Selection Algorithm (RWSA) is the simplest selection of algorithms and is commonly employed for optimization because of its adaptive and heuristic search capability. The RWSA is used in first stage of genetic algorithms wherein individual genomes or chromosomes are chosen from the population for later breeding, requiring hundreds or thousands set of samples. The process of selecting the lucky chromosomes is done by filtering the entire populations using the probabilistic fitness function. Moreover, genetic algorithm runs through many complex stages such as selection, crossover, mutation, recombination and stop criterion that requires large set of data for manipulation, validation and reliability – the larger the population, the better and more reliable results are. In the absence of large data, genetic algorithm becomes unreliable and optimization process becomes biased. To perform optimization for small populations, without going through rigorous process of genetic algorithm, a lax or brute force implementation of the roulette wheel selection algorithm is possible without doubt for reliability and validity problem.

ALGORITHM *Reversed Roulette Wheel Selection Algorithm (L[1….12])*
//Combining RWSA and Linear Ranking Algorithm
//**Input**: Collected Performance Matrix
//**Output**: New Personalized Learning Sequence
S ← 0;   // Computing the fitness function
for i ← 1 **to** N **do**
    compute(FV_i)
    S = S + FV_i
for i ← 1 **to** N **do** //sort and rank FV followed by Lesson ID accordingly
    perform linear ranking ((FV_i + L_i)
for i ← 1 **to** N **do** //compute the cumulative FV according to its rank
    compute cumulative FV (cFV_i)
generate random number **r** from interval (0,S)
for i ← 1 **to** N **do** **//**identifying lesson with misconceptions
    if $r_i \geq cFV_i$, select L_i
    return {L_i, L_{i+1}, …, L_N}

Figure 4.1: Reversed Roulette Wheel Selection Algorithm

Typically, RSWA works by arranging the chromosomes according to their fitness function. Each individual was assigned a segment of roulette wheel. The size of each segment in the roulette wheel is proportional to the value of the fitness of the individual – the bigger the value, the larger the segment is (Goldberg, 1999). Then, the virtual roulette wheel was spun. The individual who corresponded to the segment, where the roulette wheel stopped was then selected. The process was then repeated until the desired number of individuals was selected. The individuals with higher fitness selection value have higher probability of selection, which could create biased selections towards high fitness individuals. The best individuals in the population could also be missed in this process. There was no guarantee that good individuals would be selected. However, by improving the algorithm performance and incorporating the linear ranking, the biases in selections are eliminated as shown Figure 4.1 This is called the reversed roulette wheel selection algorithm.

The algorithm of Reversed Roulette Wheel selection algorithm in Figure 4.1 is started by selecting the entire populations (set of Lessons) as candidates for elimination. Each lesson has its fitness value and feed into the RWSA and linear selection algorithm. The results are compared to the random numbers *r*, which is generated by the system. Random numbers is used as a filtering mechanism commonly used in the selection, approximation and optimization process. The lesson with fitness value and higher than the random number is eliminated while the lesson with lower fitness value which perceived to have learning difficulty is maintained (reverse implementation). The retained lessons then undergo recombination process. The flow and process is repeated until it reach third generation.

In the e-learning implementation, chromosomes or individual is denoted by lesson L_i, where *L* stands for lesson and *i* refers to lesson number on the curriculum vector. Each lesson had fitness value that dynamically changed according to the learner's various performance matrix during the learning process. A high fitness value indicated that a high competency level had been achieved. Thus, in e-learning, the Reverse Roulette Wheel Selection algorithm worked in a premise "that the lower the fitness value, the more chances it will be maintained and selected for reinforcement." Lessons with low fitness level were maintained in which a reversed mechanism of a typical RWSA is implemented.

The second step of the algorithm was to sort out` the population by increasing and ranking accordingly the fitness. The fitness assigned to each individual depend only on its position in the individual rank and not on the actual fitness values. The ranking was linear so that it eliminated or overcame the scaling bias or problem of a typical roulette wheel selection algorithm. The bias was the stagnations in the case where selective pressure was too small or premature. The convergence where selection had caused the search to narrow down too quickly was indicated by Baker (1989). Rank *N* was assigned to the best individual while rank 1 to the worst individual. Ranking introduced a uniform scaling across the population and provided a simple and effective way of controlling selective pressure.

The third step of the algorithm was to compute the accumulated fitness value of an individual or lesson. Accumulated normalized fitness was the sum of its own fitness value plus the fitness values of all the previous individuals. The accumulated fitness of the last individual should be one, otherwise something had gone wrong in the normalization step. The fourth step of the algorithm was the generation of random number between 0 and 1 which filtered the selection process; whereas the last part selected the individual whose accumulated normalized value was less than the cumulative *S*. The algorithm recommended the set of lesson for further learning.

The reversed RWSA mechanisms selected individuals with less than accumulated normalized values so that the lesson with lower probability would be selected for recombination process and subjected for reinforcement process. Lesson with lower probability compared to cumulative *S*, indicated a presence of misconceptions or low competency level and the need to undergo mastery.

4.3 Modeling the Fitness Function

A fitness function *fv*, is a particular type of objective function that is used to summarize, as single figure of merit, how close a given design solution in achieving the set aims. Normally, after each round of testing or simulation, the idea is to delete the ‘n’ in the best performing population and retain the worst. The new ‘n’ undergoes mastery and reinforcement as a new breed from the design solution. Each design solution needs to be awarded a figure of merit or numerical value to indicate how close it came in meeting the overall specification. It is generated by applying the fitness function to the test or simulation, obtaining the minimized solution towards the goal. This reversed mechanism is implemented so that the lesson with higher fitness value will be eliminated while the lessons that presumably failed, or lesson with low competency level will be retained. Lessons with low performance indicator will undergo mastery and reinforcement in the learning process.

In designing the fitness function of the proposed system, the fitness function was mutable, as in niche differentiation or the co-evolution of the set of test cases. Computing the fitness function of the Reverse Roulette Wheel Selection algorithm depends dynamically on three performance parameters that have been formulated: *examination performance*, *study performance,* and *review performance* of the learner. To compute dynamically the *fv* of students, the following mathematical notations were used.

4.3.1 Mathematical Notations

fv → fitness value

L_i → refer to Lesson ($i=1\ldots..12$)

W_i → ideal weight of L_i

IdT_i → allotted time for reading the e-learning materials for L_i

S_i → actual time spent in reading L_i of student

$P(L_i)$ → actual probability weight of the L_i in reading the e-learning materials.

$RQ(L_i)$ → number of random questions for L_i

N → number of L_i

Tdf → total degree of difficulty for L_i

Qdf → score or degree of difficulty for each question Q

$ExPer(L_i)$ → individual performance value for L_i

S_{St} → status of study (either 1 or 0) for L_i

NW_{i} → normalized weight for Lesson i

$SP(L_i)$ → study performance for each Lesson i

Allow_time → minimum allowable time, the student can re-visit/re-read or review the learning materials usually set to 10 for L_i

Time_Reviewed → the number of times student visited the learning materials L_i

R_{ST} → the value is 0 (> the allowed time) or 1 (< the allowed time) for L_i

P_{TA} → probability of each individual in reviewing the learning materials of L_i

irs → ideal review score which is set to 1

$Actual\_irs(L_i)$ → the resulting difference of ideal review score of and probability of reviewing the materials of L_i

dv → discriminating value

Review_points → review equivalent of L_i

Review_Perf → normalized review points of L_i

Pt → passing threshold (set to 75) for the course

FScore → Final Score of students based on Examination Performance.

4.3.2 Examination Performance

Examination results are direct information about a student's knowledge. The *examination performance* was dynamically constructed based on student background in reading the learning materials. Questions were provided to cover the topics that were most recently completed. Each question had a level of difficulty; answering correctly a harder question demonstrates a higher ability than correctly answering an easier question.

Equation 4.1: Actual Lesson Weight Probability computed the actual weight based on individual time spent in reading a lesson over the total time spent reading the materials. The $P(L_i)$ *is* directly proportional to S_i. Higher weight to L was awarded to students who allotted more time in reading a particular learning object. Based on the $P(L_i)$, a personalized random questions are extracted from the database.

$$P(L_i) = \frac{S_i}{\sum_{i=1}^{L} S_i} \tag{4.1}$$

Equation 4.2: Random Questions was used to compute the number of random questions or items RQL_i, which were extracted from each Lesson. The total question was sixty items.

$$RQL_i = 60 * P(L_i) \tag{4.2}$$

Equation 4.3: Individual Examination Performance *ExPer(L_i)*, the score was equal to the sum of the correct item difficulty factor *df*, divided by the total difficulty factor T_{df} .

$$ExPer(L_i) = \left(\frac{\sum_{i=1}^{N} Qdf\,(L_i)}{Tdf\,(L_i)} \right) \tag{4.3}$$

Equation 4.4: Overall Performance *FScore*, was the accumulated *Exper(L_i)* which represents the overall competency level. If the *FScore* is greater than the passing threshold value P_t, or competency level which is 75, then the learner can no longer undergo reinforcement and mastery learning.

$$FScore = \sum_{i=1}^{L} \left(\frac{\sum_{i=1}^{N} Qdf\,(L_i)}{Tdf\,(L_i)} \right) * 100 \tag{4.4}$$

Table 4.1 shows how the different equations work to compute examination performance., First, the system collected dynamically the time spent in reading the materials S_i for L_i. Using Equation 4.1, the column $P(L_i)$ was computed proportionately by individual S_i over the overall S_i. The PL_i was the probability of L_i which determined the number of random questions extracted from the Item Bank.

Sixty (60) items were needed to generate summative examination that were randomly selected among the twelve lessons. Equation 4.2 was used to compute RQL_i . The RQL_i for L_1 for example, had 6 randomly selected questions with different difficulty level. The six questions extracted had a degree of difficulty 1, 1, 1, 1, 1.5 and 2 and which totalled to 7.5 which was also the total degree difficulty factor for L_1 , $TdfL_1$. Out of six questions, four accumulated a score of five, $QdfL_1$ with 1, 1, 1 and 2 respectively. To compute the examination performance for each L_i, Equation 4.3 was used. Similarly, this process was repeated for L_2 to $L_{12.}$ The final score *FScore* was computed using Equation 4.4 with a total of 60.80.

Table 4.1: Extraction of Examination Performance

L_i	S_i	$P(L_i)$	$RQ(L_i)$	$Tdf(L_i)$	$Qdf(L_i)$	$ExPer(L_i)$
L1	145	0.10	6	7.5	5	66.67
L2	125	0.09	5	7.5	6	80.00
L3	130	0.09	6	7.5	3	40.00
L4	135	0.10	6	7.5	3	40.00
L5	100	0.07	4	6	5	83.33
L6	100	0.07	4	5.5	3	54.55
L7	80	0.06	3	4	2	50.00
L8	90	0.06	4	5	3	60.00
L9	120	0.09	5	5	4	80.00
L10	100	0.07	4	4	2	50.00
L11	150	0.11	6	4	3	75.00
L12	120	0.09	5	4	2	50.00
Total	1395	1.00	60	67.5	41	60.80

4.3.3 Study Performance

Study performance refers to the main interaction that the students have with the learning environment through viewing or listening to the course materials in multimedia forms. The study performance SPL_i, was used to judge how much comprehension the students gained through this activities. A topic was usually presented in multiple pages and each topic was assigned a weight, W_i, which corresponded to its importance.

Equation 4.5: Study Status S_{St}, is executed if the actual time spent in reading the materials was greater than the ideal time required.

$$S_{St} = \begin{cases} = 1 \; if \; S_i < IdT_i \\ = 0 \;\; otherwise \end{cases} \qquad \textbf{(4.5)}$$

The study performance status S_{St} was either zero (0) or one (1). Equation 4.5 gave weight to students that maximized their allowable time in reading the learning materials. Students who read the learning materials less than IdT_i, were considered to have higher comprehension level. The lower the S_i , the better for students who read the learning materials. The normalized weight of L_i, NW_i, was calculated based on the S_{St} and actual weight of the learning materials, W_i.

Equation 4.6 Actual Weight W_i**,** was computed based on the perceived importance of the topic in the curriculum which was defined prior to this study.

$$NW_i = \sum_{i=1}^{L} W_i * S_{St}(\mathrm{L}_i) \qquad \textbf{(4.6)}$$

Equation 4.7: Study Performance *SP(L$_i$)*, is allotted for each lesson and computed by multiplying the normalized weight $NW_{i,}$ by five. Five was the maximum score of study performance. Students that exceeded the allowable time, $IdT_{i,}$ could have lower study performance but higher review performance.

$$SP(L_i) = 5 * NW_i \qquad \textbf{(4.7)}$$

For the purpose of computing the study performance, Table 4.2 was used to simulate equations presented in this section. Initially, the weight of each lesson W_i (column 2) and an ideal time IdT_i ,(column 3), of 120 minutes were given. Column 4 to Column 6 was dynamically populated by extracting columns from Table 4.1 while Column 7, the S_{ST} was determined by the condition stated in Equation 4.5. The normalized weight NW_i , was computed using Equation 4.6 while study performance for each L_i, $SP(L_i)$ was computed using Equation 4.7.

Table 4.2: Extraction of Study Performance

1	2	3	4	5	6	7	8	9
L_i	W_i	IdT_i	S_i	$P(L_i)$	$RQ(L_i)$	S_{ST}	NW_i	$SP(L_i)$
L1	0.12	120	145	0.10	6	0	0.00	0.00
L2	0.10	120	125	0.09	5	0	0.00	0.00
L3	0.03	120	130	0.09	6	0	0.00	0.00
L4	0.08	120	135	0.10	6	0	0.00	0.00
L5	0.10	120	100	0.07	4	1	0.10	0.50
L6	0.07	120	100	0.07	4	1	0.07	0.35
L7	0.12	120	80	0.06	3	1	0.12	0.60
L8	0.07	120	90	0.06	4	1	0.07	0.35
L9	0.08	120	120	0.09	5	1	0.08	0.40
L10	0.08	120	100	0.07	4	1	0.08	0.40
L11	0.10	120	150	0.11	6	0	0.00	0.00
L12	0.05	120	120	0.09	5	1	0.05	0.25
	1.00	**1440**	**1395**	**1.00**	**60**	**7**	**0.57**	**2.85**

The overall study performance was the sum of all *SP(L$_i$)* making it 2.85. This is shown in Table 4.2. In order to read the reading materials and if all S_i is greater than the ideal time $IdT_{i,}$ the overall study performance is equal to zero otherwise it would compute proportionately the maximum study performance which is five.

4.3.4 Reviewed Topics Performance

The *review topics performance* score on a topic records how much the student had to review the topic. It was based on how many times the topic was reviewed and how much of the materials were viewed. The range of the review score was from 0 to 1 for each topic. Each time a student reviewed the topic, a discriminating value *dv*, of 0.1 was deducted to its ideal review score *irs*, initially set to 1.

The students were allowed to navigate the learning materials up to 10 times *(Allow_time*). The bases of this frequency was considerably taken and this was higher than the average time students reviewed during the initial testing. Frequency of clicking the arrow back and forth in the e-learning module was considered as reviewing the learning materials *(Time_Reviewed)*. The value was dynamic for each student since each learner had his/her own pace of reading the e-learning materials.

Equation 4.8: Review Status R_{ST}, was set to 1 if the number of times was less than the *Allow_time*, otherwise zero. Every time a student exceeded *Allow_time* in each L_i, his/her R_{ST} was automatically set to zero.

$$R_{ST}(\mathrm{L_i}) = \begin{cases} 1 \text{ } if \text{ } Time\_Reviewed < Allow\_Time \\ 0 \qquad\qquad\qquad\qquad\qquad otherwise \end{cases} \tag{4.8}$$

Equation 4.9: Probability of Student Review P_{TA}, is responsible in the system to compute the actual probability based on the actual reviewed time and the allowable time set in the system.

$$P_{TA}(L_i) = \frac{Time\_\mathrm{Re}viewed(L_i)}{Time\_Allow(L_i)} \tag{4.9}$$

Equation 4.10: Actual Ideal Review Score $Actual_{irs}$, was initially set to one; each time a student reviewed the learning materials, a 0.1 was deducted from his/her *irs* until it reached zero or negative.

$$Actual_{irs}(L_i) = irs - P_{TA}(L_i) \tag{4.10}$$

Equation 4.11: Discriminating Value *dv*, was a condition that used to convert negative $Actual_{irs}$ to zero. Negative $Actual_{irs}$ should be discouraged and should be eliminated to avoid distortion during the normalization of the overall review performance.

$$dv(L_i) = \begin{cases} Actual_{irs} & if\ the\ irs(Li)\ is\ positive \\ 0 & if\ the\ irs(Li) is\ negtaive \end{cases} \quad \textbf{(4.11)}$$

Equation 4.12: Individual Review Points *Review_Points(L_i)*, in the e-learning module is computed by dividing the individual discriminating value of the lesson and the total number of lesson to normalize the distribution of the rewards for reviewing. The total number of lesson was twelve.

$$\mathrm{Re}view\_Po\mathrm{int}\,s(L_i) = \frac{dv(L_i)}{L_N} \quad \textbf{(4.12)}$$

Equation 4.13: Overall Review Performance *Review_Perf*, was used to compute the overall rewards for reviewing. The rewards is proportionately distributed. The weight of review performance matrix was 5.

$$\mathrm{Re}view\_Perf\,(\mathrm{L_i}) = \sum_{i=1}^{L} 5 * \mathrm{Re}view\_Po\mathrm{int}\,s(L_i)\,. \quad \textbf{(4.13)}$$

For the purpose of illustrating the list of equations presented in this section, simulated data were used as shown in Table 4.3. Initially, the system allowed the student to go back and forth in the learning materials 10 times as shown in Column 2. Column 3, labeled as *Time_Reviewed* was dynamically populated by the system and these data were collected by recording the number of times the students accessed the pages of the e-learning objects. Column 4 was populated using the condition in Equation 4.8 while column 5 was populated by performing Equation 4.9. The ideal review score *irs*, was constant with a value of one as shown in Column 6. Column 7 was populated as a result of performing Equation 4.10 while Column 8 was used to perform Equation 4.11 to eliminate the noise or the negative values. Column 9 was performed using Equation 4.12 which divided the discriminating value *dv*, by *N* while column 10 was populated by multiplying the results of Column 9 by five for individual L_i. The overall student review performance in this simulations was 2.92 as computed by Equation 4.13. Based on simulations, if a student did not review the learning materials and showed high level of comprehension and understanding then the maximum review score of five was is given, otherwise, it was computed proportionately for individual L_i.

These three scores of *examination performance*, *study performance*, and *reviewed topics performance* were then combined into a single value called fitness value, which indicated how well the topic was learned. The *examination performance* score is the most important among the three. When a student achieved a reasonably high examination score, greater than equal to 75, which is the passing threshold *Pt*, then the other score do not matter much then the examination performance score which is denoted by Equation 4.4 becomes the final mark, *FScore*, of the student. However, if the *examination performance* score was less than the passing threshold, *Pt*, then the other factors became relevant, producing a single numerical value called fitness value for each Lesson, ***fv(Li)***, in the e-learning module.

Table 4.3: Extraction of Review Performance

1	2	3	4	5	6	7	8	9	10
Lesson_No	Allow_time	Time_Reviewed	R_{ST}	P_{TA}	irs	Actual-irs	dv	Review_Points	Review_Perf
L1	10	5	1	0.5	1	0.50	0.50	0.04	0.21
L2	10	4	1	0.4	1	0.60	0.60	0.05	0.25
L3	10	3	1	0.3	1	0.70	0.70	0.06	0.29
L4	10	2	1	0.2	1	0.80	0.80	0.07	0.33
L5	10	1	1	0.1	1	0.90	0.90	0.08	0.38
L6	10	1	1	0.1	1	0.90	0.90	0.08	0.38
L7	10	1	1	0.1	1	0.90	0.90	0.08	0.38
L8	10	3	1	0.3	1	0.70	0.70	0.06	0.29
L9	10	12	0	1.2	1	-0.20	0.00	0.00	0.00
L10	10	14	0	1.4	1	-0.40	0.00	0.00	0.00
L11	10	8	1	0.8	1	0.20	0.20	0.02	0.08
L12	10	2	1	0.2	1	0.80	0.80	0.07	0.33
									2.92

Equation 4.14: Fitness Function *fv*, is derived from three performance parameters: *examination*, *review*, and *study* matrix.

$$\mathrm{fv}(L_i) = Exper(L_i) + \mathrm{Re}view\_Perf(L_i) + SP(\mathrm{L_i}) \quad \textbf{(4.14)}$$

Equation 4.15: Normalization of Fitness Value, means dividing the fitness values of each individual by the sum of all fitness, so that the sum of all resulting fitness values equals 1.

$$\text{Normalized\_fv}(\mathrm{L_i}) = \frac{\mathrm{fv}(L_i)}{\sum_{i=1}^{L} \mathrm{fv}(L_i)} \qquad \textbf{(4.15)}$$

4.4 Personalized Learning Sequence Process

After successfully reading the learning materials, all learners took a summative examination to personalize their learning paths and determine which topics or lessons would be selected for further reading. Students who had scored with an overall average of 75 for the first time on their summative examination were considered to have passed the course. This was computed using Equation 4.4. On the other hand, those students who failed undergoes some mastery and reinforcement learning. For the purpose of discussion, a simulated table was used to demonstrate how a personalized learning sequence were recommended by the system using different equations discussed in Section 5.3.1. It was assumed that a student did not successfully pass the first summative examination. The following steps were be executed to dynamically populate Table 4.4:

Step 1: Various performance matrices which includes performance *(Column 2 using Equation 4.3)*, study performance *(Column 4 using Equation 4.7)*, and review performance *(Column 3 using Equation 4.12)* of individual L_i, were extracted from various tables in the database to have a single numerical value called *IndividualFV (column 5 using Equation 4.14).* The individual fitness value, *IndividualFV*, was then normalized. The end value of the normalized table should always equal to one otherwise an error would have occurred during the normalization process *(Column 6 using Equation 4.15).* All these data in the system had dynamically collected for the purpose of individually profiling the students.

Step 2: The normalized fitness value was sorted and underwent a process of linear ranking as seen in *Column 7* and *Column 8* of the table.

Step 3: The linear sequence would be cumulatively added until it reached the last L_N *(Column 9)* to form the individual cumulative fitness value of L_i.

Step 4: The computer would generate a number between 0 and 1 as seen in *Column 10*.

Step 5: The failed remarks in *Column 11* would then extract the linear sequence of *Column 8* populating *Column 12.*

The system eliminated lessons that had achieved the competency level and then retained lessons with perceived learning difficulty. With this, a new learning sequence $L_3 \rightarrow L_{10} \rightarrow L_{12} \rightarrow L_{7,}$ was recommended by the system. The e-learning system replaced the default lesson outline and activated the sequence. The students underwent reinforcement level 1 and mastery learning. This process was repeated until the third generation as discussed in the Section 2.7.2. It could be noticed that the proposed learning path or sequence could simultaneously consider the curriculum difficulty level and the curriculum continuity of the successive curriculum while implementing personalized learning sequence in the learning process. In this way, the system guaranteed that students would pass the e-learning course as it gradually eliminates lesson while narrowing the gap of not getting a passing competency level. The results were heuristic yet it guaranteed that new learning sequence became smaller as the process approached the stop criterion. Instead of recommending all the lessons with failed numerical value, the system relied on the random numbers as filtering mechanism. Once a personalized learning sequence was recommended by the system, the students were directed to undergo mastery and reinforcement process.

Table 4.4: Personalized Matrix (Level 1)

1	2	3	4	5	6	7	8	9	10	11	12
Lesson_No	Exam_Perf	Review_Perf	Study_Points	IndividualFV	Normalized fv	Linear_R	Linear_Sequence	Cumulative Value	Random	Remarks	New_Sequence
L1	66.67	0.21	0.00	66.88	0.09	0.05	L3	0.05	0.89	Failed	L3
L2	80.00	0.25	0.00	80.25	0.11	0.05	L4	0.11	0.03	Passed	
L3	40.00	0.29	0.00	40.29	0.05	0.07	L10	0.18	0.63	Failed	L10
L4	40.00	0.33	0.00	40.33	0.05	0.07	L12	0.25	0.49	Failed	L12
L5	83.33	0.38	0.50	84.21	0.11	0.07	L7	0.32	0.61	Failed	L7
L6	54.55	0.38	0.35	55.27	0.08	0.08	L6	0.39	0.11	Passed	
L7	50.00	0.38	0.60	50.98	0.07	0.08	L8	0.47	0.07	Passed	
L8	60.00	0.29	0.35	60.64	0.08	0.09	L1	0.56	0.33	Passed	
L9	80.00	0.00	0.40	80.40	0.11	0.10	L11	0.67	0.29	Passed	
L10	50.00	0.00	0.40	50.40	0.07	0.11	L2	0.78	0.24	Passed	
L11	75.00	0.08	0.00	75.08	0.10	0.11	L9	0.89	0.36	Passed	
L12	50.00	0.33	0.25	50.58	0.07	0.11	L5	1.00	0.29	Passed	
				735.31	1.00						

4.5 Rule-Based Reinforcement Process

The basic idea of reinforcement theory (RL), is to reinforce behaviors and remediate problems during learning process in the form of rewards and punishments. For example, students realizes that if they do well on assignments, then they get rewards. However, students who realize that if they do not submit assignments on time, then demerits will be given as punishments. This is similar to the "Coach Dilemma or Coach Problem" in sports like football wherein players are punished by the coach if they are not on time. What does a coach do? The standard answer is extra exercise. At the end of the session, the coach identifies the tardy players and make them run extra laps or do push-ups.

Table 4.5: Rule-Based Reinforcement System

Lesson 1:
if($weights < 100) $nItems = 1;
if($weights < 80) $nItems = 2;
if($weights < 70) $nItems = 3;
if($weights < 60) $nItems = 4;
if($weights < 50) $nItems = 5;
	Lesson 7:
	if($weights < 100) $nItems = 1;
	if($weights < 80) $nItems = 2;
	if($weights < 70) $nItems = 3;
	if($weights < 60) $nItems = 4;
	if($weights < 50) $nItems = 6;

Lesson 2:
if($weights < 100) $nItems = 1;
if($weights < 80) $nItems = 2;
if($weights < 70) $nItems = 3;
if($weights < 60) $nItems = 5;
if($weights < 50) $nItems = 7;
	Lesson 8:
	if($weights < 100) $nItems = 1;
	if($weights < 80) $nItems = 2;
	if($weights < 70) $nItems = 3;
	if($weights < 60) $nItems = 4;
	if($weights < 50) $nItems = 6;

Lesson 3:
if($weights < 100) $nItems = 1;
if($weights < 80) $nItems = 2;
if($weights < 70) $nItems = 3;
if($weights < 60) $nItems = 4;
if($weights < 50) $nItems = 5;
	Lesson 9:
	if($weights < 100) $nItems = 1;
	if($weights < 80) $nItems = 2;
	if($weights < 70) $nItems = 4;
	if($weights < 60) $nItems = 6;
	if($weights < 50) $nItems = 9;

Lesson 4:
if($weights < 100) $nItems = 1;
if($weights < 80) $nItems = 2;
if($weights < 70) $nItems = 3;
if($weights < 60) $nItems = 4;
if($weights < 50) $nItems = 5;
	Lesson 10:
	if($weights < 100) $nItems = 1;
	if($weights < 80) $nItems = 2;
	if($weights < 70) $nItems = 3;
	if($weights < 60) $nItems = 5;
	if($weights < 50) $nItems = 8;

Lesson 5:
if($weights < 100) $nItems = 1;
if($weights < 80) $nItems = 2;
if($weights < 70) $nItems = 3;
if($weights < 60) $nItems = 5;
if($weights < 50) $nItems = 8;
	Lesson 11:
	if($weights < 100) $nItems = 1;
	if($weights < 80) $nItems = 2;
	if($weights < 70) $nItems = 3;
	if($weights < 60) $nItems = 5;
	if($weights < 50) $nItems = 8;

Lesson 6:	Lesson 12:
if($weights < 100) $nItems = 1;	if($weights < 100) $nItems = 1;
if($weights < 80) $nItems = 2;	if($weights < 80) $nItems = 2;
if($weights < 70) $nItems = 4;	if($weights < 70) $nItems = 3;
if($weights < 60) $nItems = 6;	if($weights < 60) $nItems = 4;
if($weights < 50) $nItems = 8;	if($weights < 50) $nItems = 5;

There were 60 rules ready to fire and match in the database to activate reinforcement files for particular student. The reinforcement files vary in each lesson depending on the available files stored in reinforcement table in the database as shown in Table 4.5 . Files or learning activities can be in the format of PowerPoint, document, gif, video, PDF, or solved problem files which were readily available for reinforcement process. Table 4.5 shows the rules of the twelve lessons. If the weight are less than the summative results in each lesson, a number of reinforcement activities were loaded to the student. For example, if the weight of Lesson 1 were less than 60, 4 *nItems* were randomly selected in the reinforcement table to be loaded on the student.

The use of random numbers during the implementation of the reversed roulette wheel selection gave the possibility that even lesson with weight higher than the passing threshold would be selected. If the student gets a perfect score for a particular lesson, all reinforcement files would be deactivated while lessons with less than 100 but greater than 80 weights would receive one reinforcement. During reinforcement, the students were required to open each blue colored links until all turns red, which indicated that the students read the reinforcement files. In case the students opened another link, the system would automatically block it to avoid the opening of several windows at the same time. This mechanism was used to avoid cascading window overloading and navigational problem. After reinforcement, the student undergoes formative to practice or check if comprehension and understanding about a particular lesson has been achieved.

4.6 Reinforcement and Mastery Learning

The personalized learning sequence, which was recommended by reversed-RWSA as shown in Section 4.4 proceeded to reinforcement process and mastery learning by reading additional learning materials (punishment) and corrective activities. Figure 4.2

shows the combined architecture of reinforcement and mastery learning to help the students in their learning process. During reinforcement process, the number of punishment was governed by the reinforcement rules as discussed in Table 4.5. The rules determined how much number of additional learning materials should be given to the students by randomly selecting from files in the reinforcement table that were stored in the database. In this model, the system chose an action a_i, (read more materials) which obtained reward r_i, (study and review matrix) and switched from state s_i to state s_{i+1} (rules). The cumulative reward r_i, was added to the average results of the summative examination.

During mastery learning, students were loaded with random questions for their individual formative examination. Students did not have the same set of questions due to random selection of items in the Item Bank database. At the end of the formative examination, the scores are prompted. The students could review their answers and directly access the link to the lesson where they could relate the questions. If needed, the students could view the explanation facilities, review answers and reload another set of examination. These helped the students to identify what they have learned well and what they needed to learn more. The specific corrective activities for students to use in correcting their learning difficulties or misconceptions were paired with each formative assessment. Most educational strategists match these correctives to every item or set of prompts within the assessment. Through this, the students were given help in identifying those concepts or skills, which were not yet mastered. The concepts or skills which are not learned would be the focus for the students to work on.

With the feedback and corrective information gained from the formative assessment, prescription of what more needs to be done to master the concepts or skill from the unit is detailed. This "just in time" correction prevented minor learning difficulties from accumulating and becoming major problems. It also gave the educational strategists practical means to vary and differentiate their instruction to better meet the students' individual learning needs.

In describing mastery learning, reducing variations in students' achievement did not imply making all students do the same. Even in those favorable learning conditions, some students undoubtedly would learn more than others, especially those involved in enrichment activities. But this is recognizing relevant, individual differences among students and then altering instruction to better meet their diverse learning needs. In e-learning implementation, mastery learning plays a very important role in molding the knowledge of the student by allowing corrective measures, random exercises and diagnostic examination. However, if its blended with reinforcement learning, it could hypothetically lead to higher learning gain.

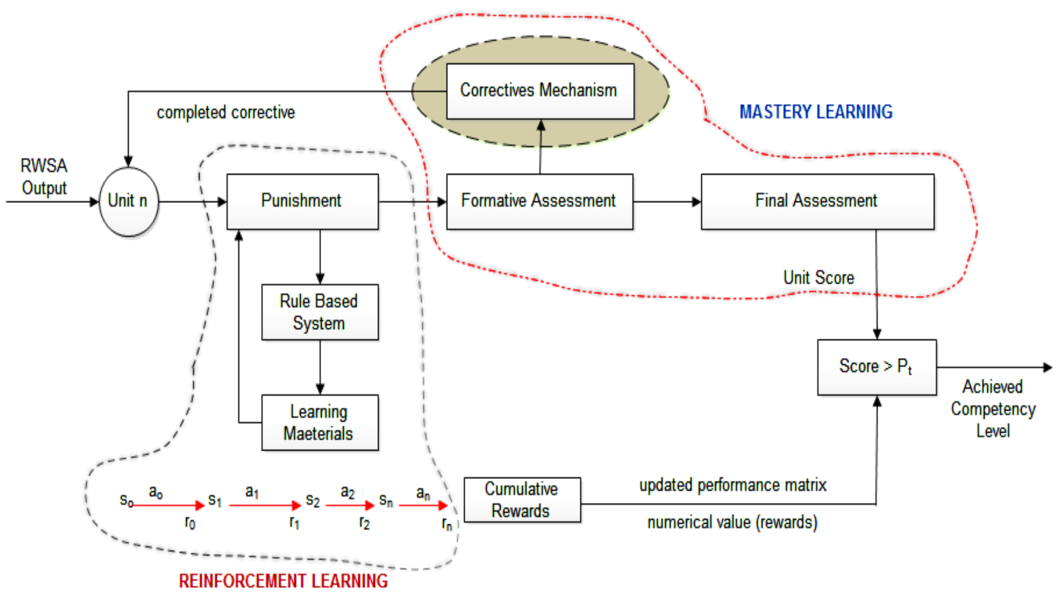


Figure 4.2: Reinforcement and Mastery Learning Model

4.7 RL and ML Database Model

The output of the reversed roulette wheel selection listed of difficulty or misconceptions of the lessons that need to be remediated immediately. The new sequence was arranged into decreasing order; topics near the passing threshold (P_t), received smaller number of reinforcement e.g. number of exercises, number of lessons and supporting materials. The RL and ML database architecture were described by Figure 4.5 as driven by the following requirements:

i. A set of recommended lessons or a personalized learning sequence was given by the system based on the results of recent summative examination. The personalized learning sequence was arranged into increasing order based on their weight or percentage. Three processes could interchangeably *(ii, iii,* and *iv)* happen but all processes would be executed or performed.

ii. A lesson could be chosen and enrichment activities be done. The fired rule that matched the weights based on reinforcement rules would randomly select learning materials from reinforcement table. The lower the weights, the more number of reinforcement was recommended by the system. The system would keep loading learning materials until all the links were deactivated. This process made sure that all the additional materials would be read by the student.

iii. The lesson would be viewed and materials would be read again by the student with learning difficulties. The lesson can be accessed from the Lesson table. In reading the materials, links and add-ins files that were incorporated and stored in the enrichment activity table were always readily available.

iv. The practice could be performed by students as many times as they want by loading random questions extracted in the Item Bank database. The learners could review their scores by viewing the details of their examination results. Incorrect answers could be linked to explanation facilities that would explain the answers. Part of the explanation facilities were links that could view specific lesson related to the current questions or topics.

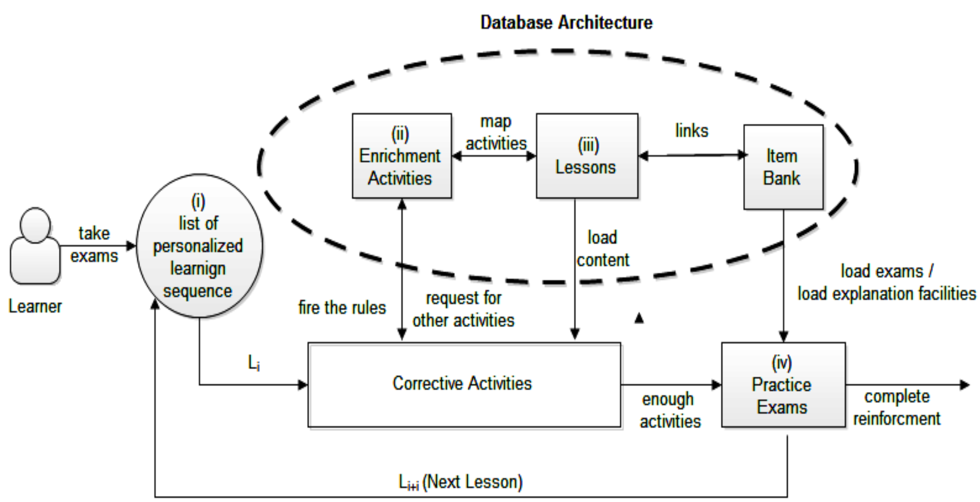


Figure 4.3: Mastery and Reinforcement Learning Architecture

As shown in Figure 4.3, two major tables from e-learning database and Item Bank database were manipulated. Hidden are 37 tables that linked together to generate several kinds of report all throughout the system implementation.

4.8 Summary

In this chapter, an improved implementation of a typical roulette wheel selection and its algorithm was discussed and presented. This includes the modeling of the fitness function of the algorithm using three performances. Several equations that have been manipulated to derive a single numerical fitness value were tested. Using simulations, it has been affirmed that the fitness value of the system which was compared to the random number generated by the computer was capable of recommending personalized learning sequence once it is implemented. The personalized learning sequence then underwent reinforcement and mastery learning based on the new architecture derived from machine learning and educational psychology.

Chapter 5: Implementation of the E-Learning Prototype

Success depends upon previous preparation, and without such preparation there is sure to be failure.

Confucius (551 – 479 BC)

Everything changes, nothing remains without change.

The Buddha(480 BCE)

I've always believed that if you put in the work, the results will come.

Michael Jordan (1963 – present)

5.1 Introduction

This chapter suggested different ways to enrich educational assessment, the content and the design in creating the e-learning prototype. These two major components are the heart and soul of the prototype because without these, the personalization and reinforcement process is not possible.

Assessment plays a very vital role in developing the e-learning system. To enrich the assessment process, 12 very useful, innovative question types in computer-based assessment were developed and stored in the Item Bank database. Two hundred eighty (280) questions were designed based on the studies of Bloom Taxonomy Staircase by Churches (2008), Taxonomy for learning, teaching and assessing by Anderson and Krathwol, (2001) and Taxonomy and categorization by Scalise and Wilson (2006). The content and design on the other hand, underwent several processes to suit the objectives in creating the system as well as the background of the students at Sirte University. In developing the content and design of the prototype, several concepts such as the design and instructional methodology were considered. The last part of this chapter are samples of live data that were extracted from the experiments and after the implementation. These extracted data demonstrate the capability of the system to personalize the learning sequence and perform reinforcement process.

5.2 Assessment Design

With dynamic visuals, sound, and user interactivity as well as adaptivity to individual test-takers and near real-time score reporting, this computer-based assessment vastly expands the testing possibilities beyond the limitations of traditional paper-and-pen tests. Through these and other technological innovations, an e-learning-based platform offers the potential for high quality formative assessment that can closely match instructional activities and goals, makes meaningful contributions to the educational delivery, and perhaps offer instructive comparisons with large scale or summative tests (Hanna & Dettmer, 2004). With the digital revolutions, it seems that technology is poised to take advantage of these new frontiers for innovation in assessment. It brings forward rich new assessment tasks and potentially powerful scoring, reporting, and real-time feedback mechanisms which can be used by the teachers and students.

One potential limitation in maximizing the benefits of computer-based assessment is the designing of questions and tasks with which computers can effectively interact, including scoring and score reporting. The question type task that is currently dominating large-scale computer-based testing and many e-learning assessments is the standard multiple-choice question, which generally includes a prompt, followed by a small set of responses from which students are expected to select the best choice. According to some researchers, ubiquitous multiple-choice testing sometimes encourages "poor attitudes toward learning and incorrect inferences about its purposes. For example, it gives the idea that there is only one right answer, and that the right answer rests solely on the teacher or test maker, and that the job of the student is to get the answer by "guessing" (Bennett, 1993, p. 24). Some cognitive theorists argue that the multiple-choice format presumes, often without sufficient basis, that complex skills can be decomposed. Moreover, some critics maintain that in practice, this format over-relies on well-structured problems with algorithmic solutions and that in theory, it builds on a view of learning that knowledge is additive rather than integrative of developing knowledge structures. This kind of task is readily scorable and offers some attractive features as an assessment format. However, if e-learning developers adopt this format as the lone focus of assessment formats in this emerging field, much of the computer platform's potential for rich and embedded assessment can be sacrificed.

Table 5.1 shows the 12 question types which were developed to enhance assessment. There were 280 questions stored in the Item Bank database ready for various assessments and grouped according to question types. Questions were formulated according to the questionnaire schema of Bloom Cogntive Taxonomy. In the Item Bank, questions were coded according to question types and question number, e.g. CSMA1 is a Complex Single Multiple Choice Question type question number 1.

Practice and assessment questions should be designed to reinforce the achievements of learning objectives. Different types of practice and test were required for different types of content such as facts, concepts, procedures, and principles. Questions formats were usually in the form of multiple choice, multiple responses, matching, ordering, and filling-in-the-blanks. In taking the practice test, feedback for the correct and incorrect answers was provided with explanation facilities. Students were usually allowed to have a self-paced e-learning provided they passed the practice examinations from prior topics to move to another. This guaranteed that learner understand the underlying concepts before proceeding to the next level.

Table 5.1: Twelve Question Types in the Item Bank

Code	Description
CSMA	Complex Single Multiple Choice Questions
FIBE	Fill-in the Blanks and Enumeration Question
MTCQ	Matching and Categorization Question
MCOQ	Matrix Completion Question
MALT	Multiple Aletrantive Question
MCID	Multiple Choice with Illustrative Diagram
MCMA	Multiple Choice and Multiple Answer Question
MATF	Multiple True or False Question
SAMC	Single Answer Multiple Question
SNCQ	Single Numerical Construction Question
SMCQ	Situational Multiple Choice Question
TOFQ	True or False Question

5.3 Assessment Questions

The 12 question types were extracted from “Question and Constraints for Technology Platform” of Scalise and Wilson (2006). It is one of the most ubiquitous and reliable taxonomy to this date with 28 example types discussed based on the seven categories of ordering which involve successively decreasing response constraints from fully selected to fully constructed. Each category of constraint included four iconic examples. References for the Taxonomy were drawn from a review of 44 papers and book chapters on item types and item designs – many of them were classic references regarding particular item types – with the intent of consolidating considerations of item constraint for use in e-learning assessment designs.

***Most* Constrained** → ***Least* Constrained**

Fully Selected — *Intermediate Constraint Item Types* — *Fully Constructed*

Less Complex ↓ **More Complex**

1. Multiple Choice	2. Selection/ Identification	3. Reordering/ Rearrangement	4. Substitution/ Correction	5. Completion	6. Construction	7. Presentation/ Portfolio
1A. *True/False* (Haladyna, 1994c, p.54)	2A. *Multiple True/False* (Haladyna, 1994c, p.58)	3A. *Matching* (Osterlind, 1998, p.234; Haladyna, 1994c, p.50)	4A. *Interlinear* (Haladyna, 1994c, p.65)	5A. *Single Numerical Constructed* (Parshall et al, 2002, p. 87)	6A. *Open-Ended Multiple Choice* (Haladyna, 1994c, p.49)	7A. *Project* (Bennett, 1993, p.4)
1B. *Alternate Choice* (Haladyna, 1994c, p.53)	2B. *Yes/No with Explanation* (McDonald, 2002, p.110)	3B. *Categorizing* (Bennett, 1993, p.44)	4B. *Sore-Finger* (Haladyna, 1994c, p.67)	5B. *Short-Answer & Sentence Completion* (Osterlind, 1998, p.237)	6B. *Figural Constructed Response* (Parshall et al, 2002, p.87)	7B. *Demonstration, Experiment, Performance* (Bennett, 1993, p.45)
1C. *Conventional or Standard Multiple Choice* (Haladyna, 1994c, p.47)	2C. *Multiple Answer* (Parshall et al, 2002, p.2; Haladyna, 1994c, p.60)	3C. *Ranking & Sequencing* (Parshall et al, 2002, p.2)	4C. *Limited Figural Drawing* (Bennett, 1993, p.44)	5C. *Cloze-Procedure* (Osterlind, 1998, p.242)	6C. *Concept Map* (Shavelson, R. J., 2001; Chung & Baker, 1997)	7C. *Discussion, Interview* (Bennett, 1993, p.45)
1D. *Multiple Choice with New Media Distractors* (Parshall et al, 2002, p.87)	2D. *Complex Multiple Choice* (Haladyna, 1994c, p.57)	3D. *Assembling Proof* (Bennett, 1993, p.44)	4D. *Bug/Fault Correction* (Bennett, 1993, p.44)	5D. *Matrix Completion* (Embretson, S, 2002, p. 225)	6D. *Essay* (Page et al, 1995, 561-565) & *Automated Editing* (Breland et al, 2001, pp.1-64)	7D. *Diagnosis, Teaching* (Bennett, 1993, p.4)

Figure 5.1: Selected Assessment Schema (Scalise & Wilson of 2006)

Out of twenty-eight example types, twelve were selected as shown in Figure 5.1. Color coded columns were adapted as deem appropriate in studying Design and Analysis of Algorithm course. The Taxonomy described and gave examples of the 28 iconic intermediate constraint item types that feature a variety of innovations in the stimulus and/or response of the observation. It allowed more freedom for the improvement of assessment design and the utilization of computer-mediated functionality. The taxonomy of constraint types included some characteristics, previous uses, and strengths and weaknesses of each type. Intermediate constraint tasks can be used alone for complex assessments or be readily composited together, bundled and treated with bundle (testlet) measurement models. The following are sample questions extracted from different question types:

5.3.1 True or False Questions

Items that required an examinee to choose an answer from a small set of response options fall into the first column of the Taxonomy table, which was the multiple choice category. Examples of four iconic types in this category are shown in Figures 5.2 to 5.5.

TOFQ7. A function $t(n)$ is said to be in $O(g(n))$, denoted $t(n) \in O(g(n))$, if $t(n)$ is bounded below by some constant multiple of $g(n)$ for all large n, i.e., if there exist some positive constant c and some nonnegative integer n_0.

[ ] True
[√] False

Figure 5.2: True or False Example

These include the simplest selected response item types that offered only two choices, such as simple true/false items or Types 1A and 1B in the *Intermediate Constraint Taxonomy* presented in Figure 5.1. In the Type 1A example, respondents were asked whether a function t(n) was bounded, given a condition true or false. The correct answer in this case was *False*. Making a selection between "*yes or true*" and "*no or false*" for a given statement is one of the simplest and most constrained selected choice formats as shown in Figure 2.5.

5.3.2 Alternative Choice Questions

Alternate choice items are similar to true/false items; however, rather than asking whether a single statement is correct or not, alternate choice offers two statements and asks the respondent to select the better option. Choices are often scenarios or cases, as shown in the Type 1B example in Figure 5.3.

MALT2. Evaluate the 2 codes below and determine which one is better? Used 99, 6, 0, 89, 30 as test data.

ALGORITHM 1

```
for i←1 to n − 1 do
    v ←A[i]
    j ←i − 1
   while j ≥ 0 and A[j ]> v do
       A[j + 1]←A[j ]
       j ←j − 1
A[j + 1]←v
```

ALGORITHM 2

```
for i←1 to n − 1 do
j←i − 1
        while j ≥ 0 and A[j ]>A[j + 1] do
        swap(A[j ], A[j + 1])
         j ←j − 1
```

[ ] Algorithm 1 runs at O(n^2) with 7 lines, the criteria of analyzing algorithm in this case uses simplicity and readability. Tracing back using the test data is straightforward however line 3 and line 6 repeatedly executed.

[ ] Algorithm 2 runs at O(n^2) with 5 lines. It eliminates redundancy and straight forward mechanism. Thus it is better to implement and simple.

Figure 5.3: Alternate Choice Example

In this type, students were shown two possible algorithmic models for computing their running time complexity and must choose the most accurate response option. In this case, the correct answer was the second option due to its simplicity.

5.3.3 Single Answer Multiple Choice Questions

In a question type where the available choices from which to select answers increase beyond two, Type 1C items are generated, which are the conventional or standard multiple choice questions with usually four or five distractors and a single correct option.

SAMC7. What is the equivalent of $\lceil \log (n + 1) \rceil$?

a. $\lfloor \log n \rfloor + 1$

b. $\lfloor \log n \rfloor - 1$

c. $\lfloor \log n \rfloor * 1$

d. $\lceil \log n \rceil + 1$

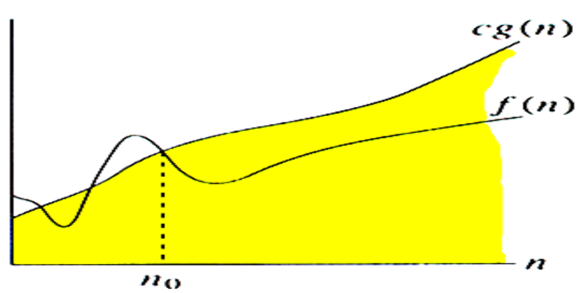
Figure 5.4: Single Answer Multiple Choice Example

The example presented in Figure 5.4 shows a list of logarithmic functions that is likely equivalent to ceiling function of log (n + 1). The answer required understanding of logarithmic law and simplifications thus the answer was *Option A*.

5.3.4 Multiple Choice with Illustrative Diagrams

Innovations in the multiple-choice category for online settings can include new response actions not common in paper-and-pen settings, such as clicking on an area of a graphical image. It can also include new media, such as sound clips which can be considered as distractors. Such new media innovations are represented in Taxonomy as Type 1D, Multiple Choice with Illustrative Diagrams. An example is given in Figure 5.5.

MCID2. Select the best definition of the graph.



[ ] A. $t(n) \le cg(n)$ for all $n \ge n_0$.

[ ] B. $t(n) \ge cg(n)$ for all $n \ge n_0$.

[ ] C. If $cg(n) \le f(n)$, $c > 0$ and $\forall$ $n \ge n_0$, then $f(n) \in \Omega(g(n))$

[ ] D. $c_2 g(n) \le t(n) \le c_1 g(n)$ for all $n \ge n_0$

Figure 5.5: Multiple Choice with Illustrative Diagrams Example

In this example, respondents must select one of the four choices that corresponded to the meaning of the graph. There were four choices to choose from. This is analogous to the standard multiple choice question with four possible responses and one correct choice, but with the mode of response involving analysis.

5.3.5 Multiple True or False Questions

The Type 2A, multiple true-false (MATF), is really an item set, or item bundle, that offers the advantage of administering many items in a short period of time. But this type has a single score over many items so that guessing is controlled within the item group. It is unlikely for a respondent to randomly guess a consistently correct over a set of items.

MATF6. Which of the following statements are True or False about criteria asymptotic notations. Select all that apply.

True	False	
[ ]	[ ]	A. Big-Oh(O) notation, $t(n) \leq cg(n)$ for all $n \geq n_0$
[ ]	[ ]	B. $O(x^4) \approx 6x^4 - 2x^3 + 5$
[ ]	[ ]	C. Omega (Ω) notation, $t(n) \geq cg(n)$ for all $n \leq n_0$
[ ]	[ ]	D. $\Omega(n)$ could be n, log n, n/1000
[ ]	[ ]	E. Thetha (θ) notation , $c_2g(n) \leq t(n) \leq c_1g(n)$ for all $n \geq n_0$

Figure 5.6: Multiple True or False Example

The example given in Figure 5.6 lists the possible criteria of asymptotic notations. In this example, the key to a successful answer was understanding asymptotic notations of computer codes. Thus, for each choice, it was necessary to examine whether it conformed to one of the rules in computing time complexity. This ruled out answers A, B and E, as the true statements to select while C and D were the false statements.

5.3.6 Multiple Choice and Multiple Answer Questions

Type 2C in the selection/identification category is the multiple answer or format, which includes, for example, an examination item that prompts examinees to select all of the elements listed that are factual statements about the greatest common divisor (GCD). The example shown in Figure 5.7 involves options 1, 2 and 3 as the correct answers.

MCMA1. Which of the facts about greatest common divisor algorithm are true. Select all that apply by using checkbox.

[√] Euclid algorithm stop at m=0 which guarantees that the second integer gets smaller with each iteration and cannot become negative
[√] The integer checking algorithm for GCD will not work if one of its input is 0
[√] The Sieve of Erathosthenes is adapted to find the prime factors of n and m in Middle School algorithm
[x] The integer checking algorithm allow negative number for n and m
[x] Middle School Algorithm allow 1 as a prime number for special case.

Figure 5.7: Multiple Choice and Multiple Answer Example

5.3.7 Complex Single Multiple Choice Questions

The final type shown in this category Selection/Identification is Type 2D, the complex multiple choice, in which combinations of correct answers are offered as distractors.

CSMA1. The following are important problem types in analysis of algorithm except:

A. Searching, string processing, graphs problems, numerical problems
B. Searching, graph problems, numerical problems, combinatorial problems
C. Combinatorial problems, numerical problems, geometric, sorting problems
D. Mathematical problems, numerical problems, geometric, sorting problems

Figure 5.8: Complex Single Multiple Example

The example shown in Figure 5.8 involves different problem types where almost all of the choices are similar, thus involving analysis. Examinees with better test-taking skills think of one option as absolutely correct or incorrect to eliminate distractors and improve their guessing ability.

5.3.8 Matching and Categorization Questions

Given the richness of media inclusion and possible new response actions in computer environments, sequencing and ranking have become popular in courseware activities in computer environments.

MTCQ2. Match the asymptotic notations from the left given the following summation rule and enter to the input box provided

[ ] $\sum_{i=1}^{n} 1$	A. linear
[ ] $\sum_{i=1}^{n} n$	B. Quadratic
[ ] $\sum_{i=1}^{n} i^2$	A. n^4
[ ] $\sum_{i=1}^{n} i^3$	B. cubic

Figure 5.9: Matching and Categorization Example

Type 3A, Figure 5.9, involves simple pair matching of item stems on the left of the screen with a set of possible responses on the right. This matching item type is a popular format in classroom-based assessment but rare in large-scale testing programs. Choices on the left should be simplified before determining which statement on the right corresponds to correct answers, thus it involves analysis and computation. This lessens guessing and can increase the performance and problem solving skill. It is recommended that such items be continuously used as a variation of conventional multiple-choice since they are easy to construct and administer. They lend themselves to testing associations, definitions and examples. They are efficient in space, have options which do not have to be repeated. Limitations for this matching type come with item-writing traps that are easy to fall into, including non-homogeneous options, such as mixing sets of things, people and places. This type of matching type also provides equal numbers of items and options, both of which make guessing easier and can bring test-taking skills into play as a nuisance, or unwanted dimension of performance.

5.3.9 Single Numerical Construction Questions

The completion category asked respondents to finish an incomplete stimulus like what is shown in Figure 5.10. Item types include single numerical constructed items, short-answer and sentence completion. Type 5A is the single numerical constructed item type, which asked examinees to calculate/simulate and supply a desired number.

SNCQ8. Using merge sort algorithm 39, 27, 44, 4, 10, 83 and 11, how many comparison using divide and conquer given the above elements of the array?

Figure 5.10: Single Numerical Short Answer Example

This item format was once assumed to be best for low task complexity but this seems perhaps an unnecessary limitation as items demanding complex problem-solving, strategy selection and solution construction can result into a single, well-defined numerical answers. This is how the item type is often used in the classroom, although often with the specification that students show their work so that the problem-solving process is more clearly elucidated for partial credit scoring and learning intervention. This is also to discourage guessing without problem solving.

5.3.10 Fill-in the Blanks and Enumeration Questions

Type 5B, short-answer and sentence completion, is sometimes called the fill-in-the-blank format.

FIBE1. Mohammed travel from London to Canada and needs to visit several states or places of Canada. What criteria of analysis of algorithm will be applicable for him to maximize and be able to visit all the places?

The criteria is :

Figure 5.11: Fill-in the Blanks and Enumeration Example

In this example, as given in Figure 5.11, students were asked to name what criteria in algorithm analysis maximizes visits of different cities. The correct answer is "optimization." The format mainly tests factual recall, as the respondent is only allowed to supply a word or short phrase. However, it seems reasonable that computer-based approaches can perhaps allow for more scoring options. In other words, an expanded outcome space, since an extensive databank of acceptable responses can be built to allows for richer use of the item.

Short answer items are presumed to reduce guessing, but there is little research to support this point. Item writing can be a big challenge in this type. Not only can the outcome space be too narrowly constructed, so as to allow for high guessing rates, but it also can be too widely conceived so that the student's answer is correct but remains quite off the topic from what is expected, or what is being measured. This is where computer-based approaches that attempt to capture and categorize or analyze a range of empirical responses may make the item type more valuable.

5.3.11 Matrix Completion Questions

Type 5D, the matrix completion format, presents a matrix of patterns with one or more cells left blank. Respondents were asked to fill the empty cells from a set of supplied answers. Matrix completion has an extensive history in intelligence measurement and has been used in various tests of pattern recognition, correspondence, and generation (Embretson, 2002).

MCOQ1. The Tower of Hanoi is a mathematical game or puzzle. It consists of three rods, and a number of disks of different sizes which can slide onto any rod. The puzzle starts with the disks in a neat stack in ascending order of size on one rod, the smallest at the top, thus making a conical shape. The objective of the puzzle is to move the entire stack to another rod, obeying the following simple rules:

a. Only one disk may be moved at a time.
b. Each move consists of taking the upper disk from one of the stacks and placing it on top of another stack.
c. No disk may be placed on top of a smaller disk.

Complete the table from given n = 7?

n	1	2	3	4	5	6	7
M(n)	1	3	7	15	31	63	

127

Figure 5.12: Matrix Completion Example

The matrix is a table or spreadsheet of correct patterns, which can be in the form of graphics, words or numbers, as well as sound clips, film clips, and animations. These are dragged to the appropriate empty cells. The item type allows for a great deal of flexibility in the task assignment, openness of response and media inclusion, and is readily computer-scorable, making it potentially powerful item type in computer environments. It can be seen that depending on what is called for in matrix completion, the matrix type can fall into a number of categories. These are reordering, substitution and construction, as well as simple completion. Thus, this type blurs the lines of the constraint-based item taxonomy. Domain-specific matrix completion tasks may be among the families of innovation most ripe for computer based applications such as shown in Figure 5.12.

5.3.12 Situational Multiple Choice Questions

The first item type listed in the construction category of the item Taxonomy is the Type 6A. This is a situational multiple choice similar to a typical multiple choice, only this time with some level of complexity.

SMCQ7. How is factorial problem similar to Tower of Hanoi, given that Factorial, $F(n) = F(n\text{-}1)\ (n)$ *for* $n > 0$ and Tower of Hanoi, $M(n) = 2M(n\text{-}1) + 1$ *for* $n > 1$.

- [ ] A. The time of factorial is linear while Tower of Hanoi is 2^n-1
- [ ] B. They both used backward substitution to solve recurrences and mathematical induction.
- [ ] C. The time of factorial is linear while Tower of Hanoi is exponential
- [ ] D. Factorial is recursive while Tower of Hanoi is not a recursive problem

Figure 5.13: Situational Multiple Choice Example

The scenarios or situational problems were given to provide in- depth analysis. Rather than having students originate and provide some portion of the answer to the question, selection choices were provided. Students were required to analyze a situation before choosing an appropriate answer. An example of this type is shown in Figure 5.13.

5.4 Bloom Taxonomy and Degree of Difficulty

The 12 question types presented in section 5.3 were categorized according to the Cognitive Bloom Taxonomy. Table 5.2 shows the question types description and the degree of difficulty *df*, for each type in different assessment formats. In formative assessment, the *df* is 1 for reviewing purposes and practice at the end of each lesson. The *df* of Bloom Cognitive examination on the other hand is also 1, to measure the cognitive improvements of the learner which is usually administered every three weeks of the training.

Table 5.2: Questions Types and their Degree of Difficulty (df)

Bloom Taxonomy *(Category)*	Question Types	Description	Formative Assessment (*df*)	Summative Assessment (*df*)	Bloom (*df*)
REMEMBER	MATF	Multiple True or False Questions	1	1	1
	MTCQ	Matching and Categorization Questions	1	1	1
	TOFQ	True or False Questions	1	1	1
UNDERSTAND	MCMA	Multiple Choice and Multiple Answer Questions	1	1.5	1
	MCID	Multiple Choice with Illustrative Diagrams	1	1.5	1
APPLICATION	CSMA	Complex Single Multiple Choice Questions	1	1.5	1
	SNCQ	Single Numerical Construction Questions	1	1.5	1
ANALYZE	SMCQ	Situational Multiple Choice Questions	1	1.5	1
	SAMC	Single Answer Multiple Choice Questions	1	1.5	1
EVALUATE	MCOQ	Matrix Completion Questions	1	2	1
	MALT	Multiple Alternative Questions	1	2	1
CREATE	FIBE	Fill-in the Blanks and Enumeration Questions	1	2	1

The *df* of summative assessment differs accordingly since it is the most important performance matrix. As the Bloom category goes down in the table, the more difficult the question is and deeper cognitive development. Each question has a level of difficulty, which is also used in updating student performance matrix. Correctly answering a harder question demonstrates a higher ability than correctly answering an easier question. *Remember* category has *df* 1 while *Understand*, *Application*, and *Analyze* category has a *df* of 1.5 while *Evaluate* and *Create* has *df* of 2.

5.5 E-learning Framework

Numerous models for curriculum changes in technology education have been implemented. This easily leads to a situation of constructive phase, followed immediately by the planning phase. This does not give enough time for conceptualization, ideation, and the evaluation of ideas. Good design and planning are very crucial to classroom-based learning program, and even more in e-learning design. In traditional learning, the most important factor to consider is the delivery of learning, whereas in e-learning, the instructional design and development of structured material can be used several times and be shared by multiple learners using varied technology.

The e-learning framework of the study is shown in Figure 5.14. It shows that technology is the central driving force of the framework. Without it, e-learning will not exist. The framework is divided into three modules: the instructional module, the social context module, and the assessment module. The instructional content module includes integration of multiple components such as content analysis and sequencing, personalization support mechanism, and the use of digital media. The social module supports the use of social network media and collaboration while the assessment module includes test and practice module, performance parameters, and profiling.

In the content module, different tools can be used to produce e-learning content, depending on which file formats will be used and how the end product will look like. Static documents such as PowerPoint and Microsoft documents can be used as simple learning resources and can be interactive if added with more sophisticated tools such as animation, videos, graphics, and simulations. Applying available courseware authoring tools and the use of graphics, text, and other media not only entice learning, but also provide a framework to organize pages and lessons for reliable navigation.

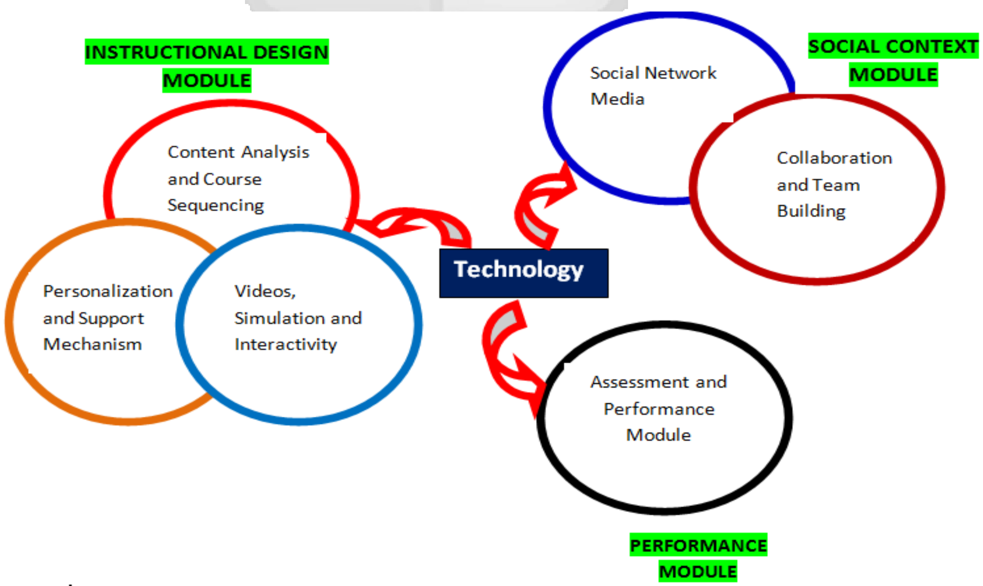


Figure 5.14: E-learning Framework of Tertiary Curriculum

(Source: Ballera & Elssaedi, 2013)

In social content module of the framework, e-learning activities can be realized by using range of communication tools – both synchronous and asynchronous. In asynchronous, tools such as e-mail, discussion forum, blogs and wikis are more appropriate tools. In the prototype, Skype, Yahoo Messenger, Windows Live Messenger, FaceBook, DropBox and TeamViewer are readily available. The concept of collaboration and team building and the use of social media is not part of the present study but worthy to mention for future use and analysis.

The performance module consists of assessment and various records of performance indicators. There were three examinations used in the study: the Bloom cognitive examination, the formative examination, and the summative examination. Mechanisms on how it dynamically populate different tables to generate reports is the main concern of this module. The assessment module can help to monitor the performance of the students and can be further used for profiling and personalizing the e-learning system.

5.6 E-learning Strategy

To support the e-learning framework discussed in the previous section, an e-learning strategy must be developed. One important element of deciding and defining e-learning strategy is the use of instructional model. It is the practice of creating "instructional experiences" which makes the acquisition of knowledge and skill more efficient, effective, and appealing.

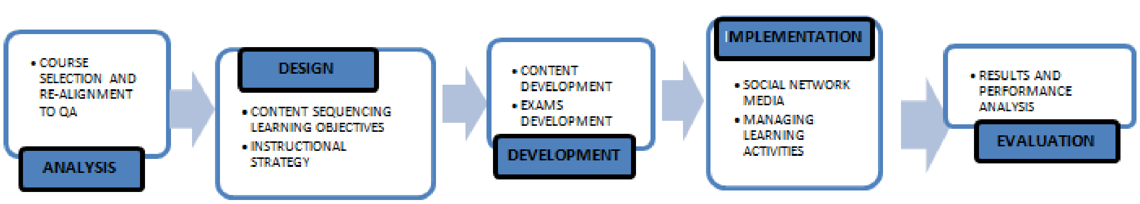


Figure 5.15: The ADDIE Model for Sirte University

(Source: Ballera & Elssaedi, 2013)

Figure 5.15 shows the ADDIE model composed of Analysis, Design, Development, Implementation and Evaluation. The model has been adapted based on its wide acceptability and use. The model has eight strategies, and these are distributed among the five phases of the ADDIE model.

i. *Course selection and Re-alignment from QA* – The course Design and Analysis of Algorithm was personally chosen by the researcher because of his 10-year experience in teaching the course. The QA approved the implementation.

ii. *Content Sequencing and Learning Objectives* – The content sequence of the course was approved by the QA in consultation with IT Staff. The identified contents together with corresponding objectives were debated upon and discussed by the cluster members. The contents were identified according to necessity, time constraints, pre-requisites, overlapping issues, and incremental learning. Content analysis shows specific learning objectives and curriculum outline based on the set requirements from the quality assurance group. This can be done by applying two methods: topic analysis and objective analysis. Topic analysis was used to identify and classify the course content while the objective analysis shows what and how the learner should learn. It also shows what and how are skills going to be developed or improved from each topic.

iii. *Instructional Strategy* – In designing the instructional strategy of the e-learning prototype, three strategies were considered; expository, application, and collaborative. The expository methods were in the form of static content such as documents and PowerPoint and interactive lessons. Proven examples with theory and illustrations of how a task can be performed using videos with a step-by-step demonstrated procedure were also considered. Application method allows learners to practice the demonstrated procedure by either modifying the inputs, doing the same procedure, and allowing the learners to take control with the application. Situational case-based exercises improve critical thinking skills by asking learners to apply knowledge and principles to the problem at hand. The collaborative method, on other hand, allows learners to have different kinds of activities such as discussion of online assignments and one-on-one tutoring. In the prototype, collaborative method is not included in the analysis although this is already considered as features of the system. This part can be analyzed for future works.

iv. *Content Development* **–** After reviewing the course syllabus, topics, and objectives, content development was considered. The primary focus of this strategy is the development of learning materials. A major challenge which providers of e-learning face is the provision of meaningful courseware that is responsive to learners and which allows them to actively participate in the learning process. It is believed by many educational strategists that a system that allows “learning by doing” arouses interest, generates motivation and provides more engaging experience for the learners. It deepens learning because students can hypothesize to test their understanding, learn by mistakes and make sense of the unexpected.

v. *Examination Development* **–** Questionnaires are developed using the Bloom Cognitive Schema found in Appendix C. These questionnaires were subjected to Cronbach’s alpha analysis for its internal consistency. There were 280 questions stored in the Item Bank database that can be readily accessed for the three examinations: Bloom, formative, and summative examination.

vi. *Social Network Media* - The rapid diffusion of social media enables users to connect with people than ever before. Students use social media at school for various purposes such as communicating, exchanging information, sharing personal experiences, and collaborating with each another. The use of social media provides a strong social component that allows the learners to work together and collaborate. However, in the prototype, these features have no bearing with the results of the study but were only added as features intended for future research works.

vii. *Managing Learning Contents* – Various mechanism in managing the contents were incorporated in the prototype to avoid navigational lost, cascading window problem, and concept overloading. Student were not allowed to open another examination if they did not pass the previous examination. They could not load examination without reviewing since the system compelled the students to study. They could not load another lesson while another lesson was open. The system also provides feedback and explanations, activated and deactivated, and of course managed the personalization and reinforcement process.

viii. *Results and Performance Analysis* – The prototype was capable of generating several reports that showed class and individual performance. The graph for cognitive development for both individual and class standing was just a mouse click away and easily generated. The final results before and after were stored in the database for generating the students' performance analysis. Trials, formative or practice results were all stored in the database. Personalized learning sequence, reinforcement files, and reinforcement level for all students could be viewed for further analysis.

5.7 Experimental Results

The experiments were conducted from March 13 to July 10, 2014. This is almost 18 weeks of implementation and was uploaded in the website. All data presented in the succeeding part of this section were live data extracted from the prototype. Screen shots have been enhanced and structured for the purpose of documentation and could be verified using the live data in the website. In this section, the assessments; Bloom cognitive examination, the formative examination, and the summative examination are discussed. The live extraction of different performance matrices to produce personalized learning sequence and their capability to reinforce learning process are also discussed.

5.7.1 Assessment Module

Assessment is generally used to refer to all activities which educational strategists use to help students learn. This is also used to gauge the students' progress (Hanna et. al, 2004). Usually, it is often divided for the sake of convenience using the following distinctions, the initial or diagnostic (Bloom), the formative (practice) and the summative (final).

5.7.1.1 Bloom Cognitive

The Bloom cognitive examination as an initial assessment was used as diagnostic measurements of the cognitive development of the students. This was conducted prior to instruction or intervention to establish a baseline from which individual student growth could be measured. The examination was activated, conducted every three weeks to gauge the cognitive development of students. Questionnaires pertaining to this were especially designed in each six categories. The six categories are: Remember (R), Understand (U), Application (A), Evaluation (E), Analysis (N), and Create (C) arranged hierarchically based on the development of cognition.

Figure 5.16 is a live screen shot of a 60-item Bloom Taxonomy examination, extracted from the Item Bank. When the item was clicked individually, a pop-up window which displayed the questions would appear. There were various mechanism that served to control or manage this particular examination. Students, for example, could not submit the examination for checking and recording unless all question were answered; each item turned blue to indicate that the item was answered. Students could review their answers provided the submit button was not yet clicked.

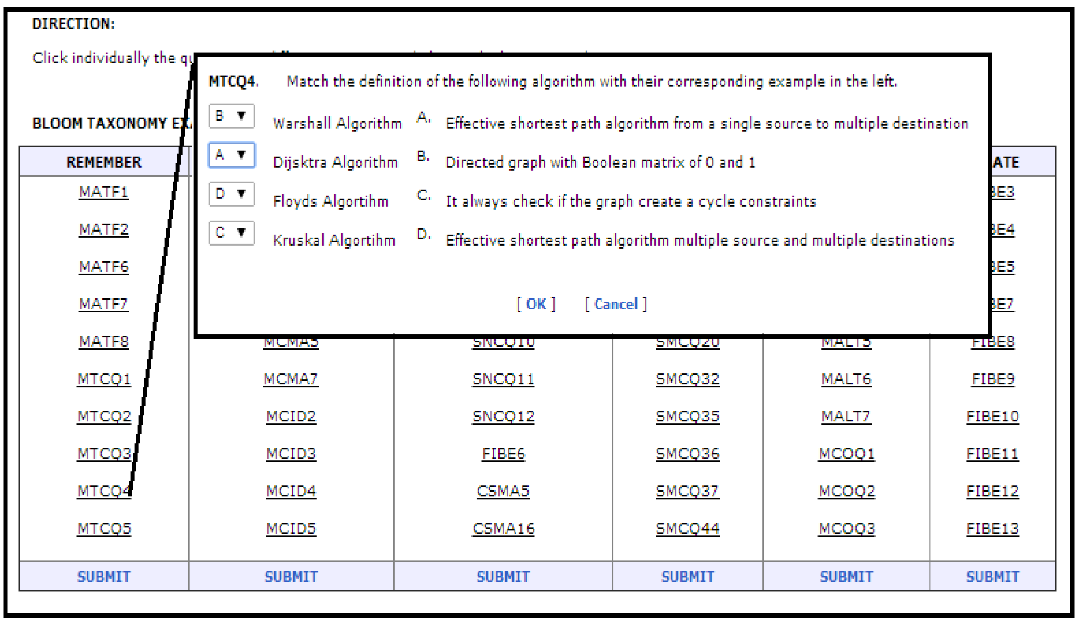


Figure 5.16: Bloom Diagnostic Exam Module

Table 5.3 is a chunk live screenshots of the Bloom Cognitive Taxonomy that displays all the scores of students in taking the examination. R1, R2, R3, R4 are the records in the "Remember Category" which pertain to the score of the first examination, second examination, third examination and fourth examination scores respectively. This is true to the same remaining five categories: Understanding (U1, U2, U3, U4), Application (A1,A2, A3, A4), Evaluation (E1,E2, E3, E4), Analysis (N1,N2, N3, N4) and Create (C1, C2, C3 , C4). The complete results can be verified in the prototype.

Table 5.3: Bloom Cognitive Examination Results

Stud_ID	R1	R2	R3	R4	U1	U2	U3	U4	A1	A2	A3	A4	E1	E2	E3	E4	N1	N2	N3	N4	C1	C2	C3	C4
111111	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1
502315	2	4	6	8	4	6	8	9	2	5	8	10	4	6	8	9	2	4	6	8	3	5	6	8
702452	1	3	6	9	2	4	6	10	2	4	6	8	2	4	6	7	1	4	5	7	0	2	3	5
802092	1	4	5	10	3	4	8	10	4	3	5	6	4	4	6	8	2	3	5	8	1	4	5	6
802098	2	5	7	9	4	5	6	8	4	6	7	8	2	3	4	5	1	2	3	4	1	2	3	4
802137	2	2	5	8	5	5	6	7	2	5	6	9	3	4	5	7	2	4	6	8	1	4	5	6
802144	1	3	5	8	2	5	5	7	4	5	6	8	3	4	6	7	3	4	7	9	1	4	8	9
802151	3	4	6	8	3	4	7	9	3	5	7	9	1	3	5	7	2	3	4	5	0	4	5	6
802178	4	4	6	8	4	5	6	8	1	3	5	8	1	3	5	9	2	3	4	5	0	4	5	6
802197	2	3	5	9	3	5	6	7	1	4	6	7	4	5	6	7	3	4	5	8	3	4	7	9
802236	5	6	7	10	4	6	7	9	1	2	6	9	2	3	7	9	2	4	6	10	2	5	8	9
802237	5	4	7	8	2	4	5	6	3	4	5	7	2	4	6	8	1	2	5	6	2	3	5	8
802491	3	5	7	9	3	5	6	7	2	3	5	6	4	5	6	7	2	4	4	5	2	3	6	8
802513	6	7	8	8	4	6	7	10	4	5	6	7	4	5	6	7	2	4	5	9	2	4	6	8
902139	3	4	6	9	5	4	8	10	4	6	8	10	4	7	8	9	1	6	7	8	2	4	6	9
902242	5	5	7	9	3	2	3	6	2	4	5	6	4	5	6	7	2	4	5	6	1	2	5	6
1002043	2	3	5	9	2	4	6	8	2	4	6	8	2	4	5	9	2	3	6	7	3	4	6	7

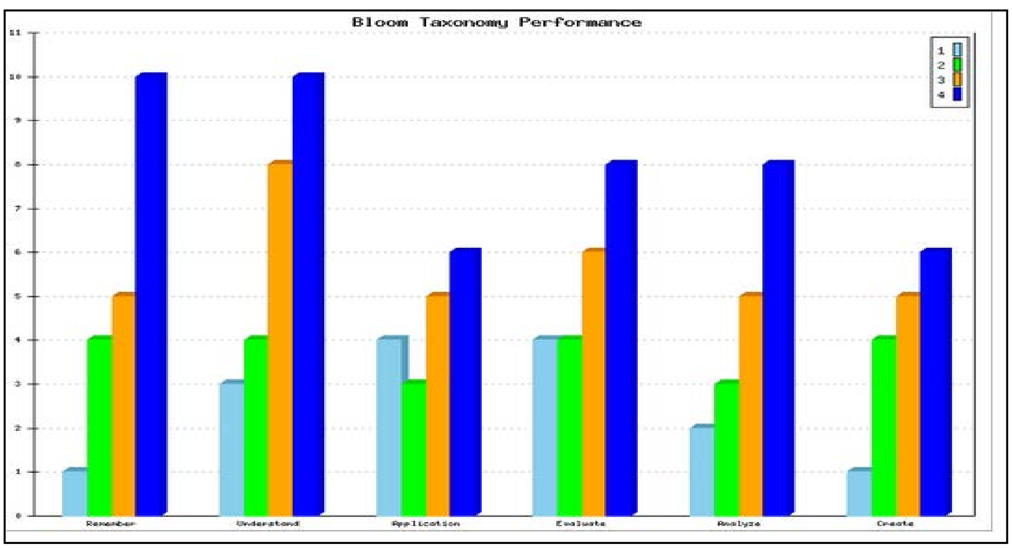


Figure 5.17: Overall Bloom's Cognitive Graph

Figure 5.17 shows the live Bloom cognitive graph indicator of student 802092, taken from the working prototype. The graph shows that the student has a poor performance in all categories in taking for the first time the diagnostic examination. This gradually improved as shown in the succeeding results. The student improved most in the *Remember* and *Understand* categories and followed by the four other categories. The student expectedly improved least in the “Create” category since it is the most difficult and highest category in the cognitive model. As observed in the fourth row, represented by color blue, all the categories showed improvement except for the “Create” category.

5.7.1.2 Formative Assessment

Formative assessment is generally carried out throughout the course specifically at the end of each lesson. Formative assessment which is also referred to as "educative assessment," is used to aid learning that usually provides feedback on a student's work and is not necessarily used for grading purposes. Formative assessments can be in the form of diagnostic, standardized tests. The formative examination serves as practice module that prepares the student into graded summative assessment. It provides information at a classroom level and to makes instructional adjustments and interventions during the learning process (Garrison & Ehringhaus, 2014). Effective teachers use formative assessment during instruction to identify specific student misunderstandings, provide feedback to students to help them correct their errors, and identify and implement instructional correctives (Cauley & McMillan, 2014).

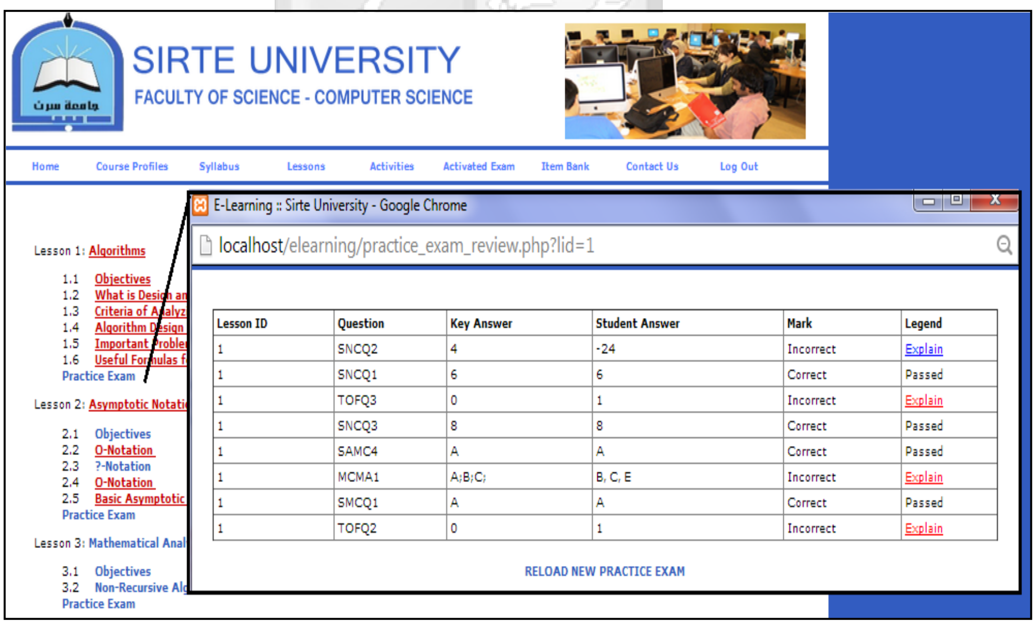


Figure 5.18: Practice Examination Module

Figure 5.18 is a live screen shot of the formative examination taken from the prototype. For each lesson, eight random questions were dynamically selected or extracted from the Item Bank at the end of each chapter. To guarantee that students would review the learning materials, several control mechanism were incorporated. Students, for example, could not proceed to succeeding lesson without passing the previous lesson. A student must accumulate a 75 or better grade to pass the formative examination. A student needed to review all the questions until all "Explain" buttons turned from red to blue. It could not load another without reviewing the failed questions and each question was linked to explanation facilities; and to a specific part of the lesson. Students could try as many times as they wanted to review the examination by reloading eight random questions repeatedly from the Item Bank.

Table 5.4 is a chunk of a live data taken from the prototype of the practice results. As shown in the table, a minimum of 6 out of 8 scores were recorded which was equivalent to 75 percent. The table did not record the results which were less than 75 percent. This compelled the students to review until a passing mark was achieved. The formative or practice was reloaded for the nth time as long as the students wanted to review the learning materials. Although the student could practice multiple times, only the first passing score was recorded. A negative one score was recorded if the student did not take the examination within the activated time frame. P_1 field refers to the result of formative for lesson one L_1, P_2 for lesson 2 or L_2 until P_{12} for lesson 12 and so on.

Table 5.4: Practice Examination Module

Stud_ID	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P11	P12	Ave_Prac
111111	-2	-2	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1.00
502315	6	7	6	8	6	7	7	7	6	8	8	8	7.00
702452	7	8	7	6	8	7	6	6	8	6	8	7	7.00
802092	-1	7	6	7	7	7	6	6	7	8	7	7	6.75
802098	8	8	7	7	7	7	7	7	8	6	8	7	7.25
802137	7	6	7	7	7	8	7	8	7	8	8	8	7.33
802144	7	8	8	7	8	7	8	7	8	8	8	7	7.58
802151	6	8	6	6	7	7	7	8	7	6	7	8	6.92
802178	6	7	6	8	6	8	6	6	8	6	7	7	6.75
802197	6	-1	6	7	7	7	6	7	6	6	7	6	6.42
802236	6	7	6	7	7	7	8	6	6	7	7	6	6.67
802237	8	7	6	8	8	6	7	7	7	8	8	6	7.17
802491	8	8	7	8	7	8	6	7	6	6	6	6	6.92
802513	7	7	7	6	6	6	7	6	7	6	7	7	6.58

Table 5.5 is a report of live chunk of trials generated from the prototype. This table records how many times students took formative assessment until they achieved certain competency level. This mechanism served as motivational perspective since the number of trial represented the level of understanding and comprehension in reading the e-learning module. T1 refers to the number of trials in taking lesson one, T2 for lesson and so on until T12.

Table 5.5: Number of Trials Before Passing the Practice Examination

Stud_ID	T1	T2	T3	T4	T5	T6	T7	T8	T9	T10	T11	T12
502315	3	4	4	4	1	6	6	6	5	4	4	5
702452	2	5	1	2	2	5	4	2	2	5	1	6
802092	5	5	4	5	3	5	1	3	5	2	5	1
802098	4	4	5	3	4	4	2	3	3	3	3	3
802137	2	2	1	5	5	5	2	5	4	4	4	5
802144	2	2	3	2	6	2	5	4	6	2	5	4
802151	5	2	4	2	4	5	3	4	5	5	3	2
802178	3	2	3	4	5	5	2	5	5	5	3	6
802197	5	4	1	4	1	2	4	6	6	3	3	4
802236	5	1	3	3	3	5	3	3	2	3	2	5
802237	5	5	2	4	1	6	4	5	4	6	5	5
802491	4	3	2	4	4	3	4	1	5	4	1	5
802513	4	5	3	2	2	2	2	5	5	4	5	6
902139	2	4	5	3	2	2	2	5	4	2	6	3
902242	3	5	4	2	5	5	4	2	4	1	4	5
1002043	2	6	3	2	5	6	4	5	2	4	2	6

5.7.1.3 Summative Assessment

Summative assessment is generally carried out at the end of a course. In an educational setting, summative assessments are typically used to assign students a course grade that sums up the teaching and learning process (NIU, 2014). Summative is often referred to in a learning context as assessment of learning. Assessment of learning is generally summative in nature and is intended to measure the learning outcomes and report those outcomes to students.

Figure 5.19 is a live screen shot of the summative or final examination from the prototype taken prior to the reinforcement learning to gather examination performance. This is an activated examination, initially with 60 items randomly selected from the Item Bank. No the same set of questionnaires was given to students since the creation and loading of the question types varied according to the time spent in reading the learning materials and to the random selection process. When clicking the item individually, a window that contains the question appeared. Students could review and change the answers as long as the submit button was not yet clicked. There were three sets of summative examination. The first set was a typical final examination that checked the overall competency level of the students while the second sets were activated after the students completed reinforcement level 1 and failed the first set. The third set referred to the final examination activated after reinforcement level 2 and the students failed the second set of examination. Examinations were automatically submitted into the system if the time had already lapsed or submitted for scoring, which prompted the students' overall score.

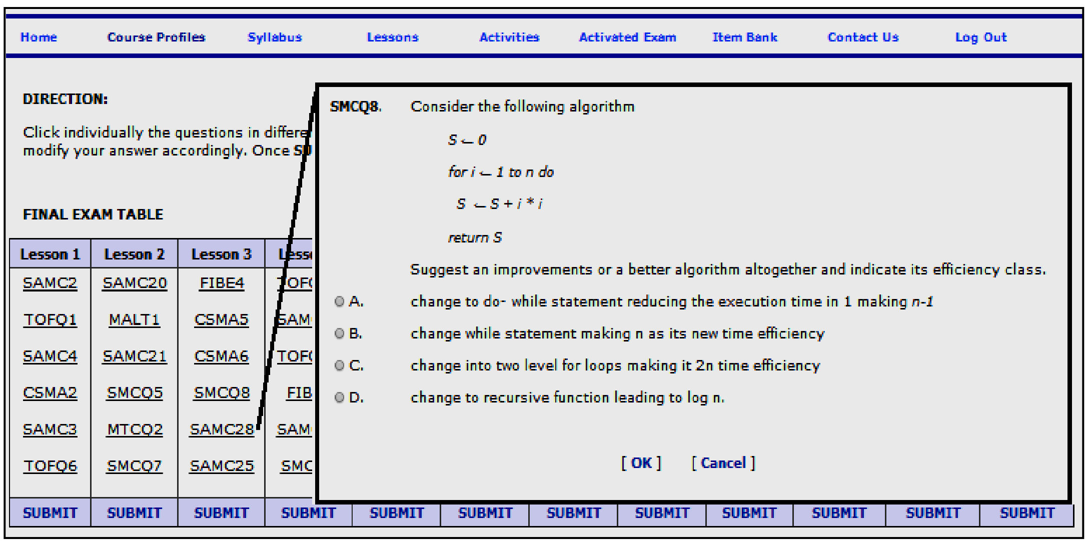


Figure 5.19: Summative Examination Module of the Prototype

Table 5.6 is a chunk of the final results of students generated and stored in the prototype database. This live data was extracted from the database that summarized vital information including the average score of formative results, study performance, review performance, cumulative rewards, teacher evaluation, the three scores of the summative examination, and the final marks. In this table, the administrator or the teacher of the class could view and analyze individually and in details all related performances of the student. The action column or Edit icon allowed the instructor to inputs additional mark to deserving students. This mechanism was a request from staff members of the faculty during initial testing and pre-survey. The F1 column shows the results of first set of examination while F2 and F3 shows the columns that stores the results of the second and the third sets respectively after reinforcement.

Table 5.6: Final Examination Results Module

Stud_ID	Ave_P	Study	Review	Rewards	T_Eval	F1	F2	F3	Final Mark	Remarks	View	Action
502315	7.00	4.60	0.83	5.43	0	75.01	0.00	0.00	75.01	Passed	ANALYZE	EDIT
702452	7.00	4.40	2.04	6.44	0	78.44	0.00	0.00	78.44	Passed	ANALYZE	EDIT
802092	6.75	3.15	1.63	4.78	0	65.81	75.20	0.00	75.20	Passed	ANALYZE	EDIT
802098	7.25	3.15	0.88	4.03	0	67.11	78.25	0.00	78.25	Passed	ANALYZE	EDIT
802137	7.33	3.90	1.08	4.98	0	74.73	63.46	59.86	59.86	Failed	ANALYZE	EDIT
802144	7.58	4.60	2.46	7.06	0	79.65	0.00	0.00	79.65	Passed	ANALYZE	EDIT
802151	6.92	5.00	1.42	6.42	7	74.93	72.60	70.63	77.63	Passed	ANALYZE	EDIT
802178	6.75	4.25	1.13	5.38	0	69.46	67.15	82.35	82.35	Passed	ANALYZE	EDIT
802197	6.42	2.55	2.33	4.88	1	73.92	73.71	74.88	75.88	Passed	ANALYZE	EDIT
802236	6.67	2.55	1.08	3.63	6	63.86	70.00	69.19	75.19	Passed	ANALYZE	EDIT
802237	7.17	4.25	0.92	5.17	0	77.14	0.00	0.00	77.14	Passed	ANALYZE	EDIT
802491	6.92	3.60	1.42	5.02	6	73.68	73.47	69.67	75.67	Passed	ANALYZE	EDIT
802513	6.58	4.00	1.38	5.38	0	66.06	72.56	80.36	80.36	Passed	ANALYZE	EDIT
902139	7.33	3.45	0.71	4.16	0	78.13	0.00	0.00	78.13	Passed	ANALYZE	EDIT
902242	7.17	3.10	1.25	4.35	0	76.66	0.00	0.00	76.66	Passed	ANALYZE	EDIT
1002043	6.92	4.50	1.13	5.63	0	66.98	85.39	0.00	85.39	Passed	ANALYZE	EDIT
1002045	7.17	3.95	1.08	5.03	6	70.49	63.48	62.99	68.99	Failed	ANALYZE	EDIT

5.7.2 Performance Extraction Module

In this section, two performance parameters were extracted from the prototype that was used to compute the fitness function of the reverse roulette wheel selection algorithm. Aside from the examination performance discussed in section 5.7.1, the review and study performance was important to determine how students review the learning materials and the level of their comprehension.

Table 5.7 is an extracted live data that shows the review performance of student ID 802592. The prototype of the system was able to extract data based on the simulation presented in section 4.3.4. As shown in the table, the student were allowed to review the learning materials and objects 10 times. This was the minimum number of times the students could review the materials based on the data gathered prior to the implementation of the prototype. The number of times students reviewed the materials was recorded to determine their review performance score. As shown on the table, lesson L_3, L_5, L_7 and L_8 received a review performance of zero since the student exceeded the allowed number of times in reviewing the materials. Other lessons proportionately computed their review performance accordingly. The maximum score of all the students' review performance is 5, and for this particular student, the accumulated total score is 1.29.

Table 5.7: Review Performance Matrix Live Sample

Lesson_No	Allow_Time	Time_Reviewed	Review	Time_Allow	irs	irs_time_allow	dv	Review_Points	Review_Perf
1	10	5	1	0.5	1.00	0.50	0.50	0.04	0.21
2	10	8	1	0.8	1.00	0.20	0.20	0.02	0.08
3	10	14	0	1.4	1.00	-0.40	0.00	0.00	0.00
4	10	3	1	0.3	1.00	0.70	0.70	0.06	0.29
5	10	11	0	1.1	1.00	-0.10	0.00	0.00	0.00
6	10	9	1	0.9	1.00	0.10	0.10	0.01	0.04
7	10	12	0	1.2	1.00	-0.20	0.00	0.00	0.00
8	10	12	0	1.2	1.00	-0.20	0.00	0.00	0.00
9	10	7	1	0.7	1.00	0.30	0.30	0.03	0.13
10	10	6	1	0.6	1.00	0.40	0.40	0.03	0.17
11	10	8	1	0.8	1.00	0.20	0.20	0.02	0.08
12	10	3	1	0.3	1.00	0.70	0.70	0.06	0.29
									1.29

Table 5.8 is the study matrix of student ID 802592. The study performance refers to the main interaction that the students have with the learning environment through viewing or listening the course materials. It is used to judge how much comprehension the student has gained while navigating the lesson and learning activities. As shown in the table, the time a student spent in reading the materials was recorded to determine how much weight was given to the learning object. The weight of the learning object dynamically changes according to the time spent in reading the materials. The lesser the time spent in reading, the higher the study performance. The design of the system gives importance to the level of comprehension of the student. It was assumed that a student who finishes in reading the materials less than the allowable time has higher level of comprehension compared to students who spent more time in reading the materials. Furthermore, lesson L_4, received a zero study points since it exceeded the time allowed in viewing the learning objects. Out of the maximum score of 5 for study performance, the student received a total of 4.6.

The two performances discussed in this section have two purposes in the system. It was used as a factor in computing the single numerical fitness function and also used as rewards points once the learners undergo reinforcement process. Twenty-seven (27) out of 41 students benefited from this mechanism and eventually passed the course.

Table 5.8: Study Performance Matrix Live Sample

Lesson_No	Weight(W)	Ideal_Time	TimeSpent(S)	Probability(Ln)	No_of_Questions	Study_Perf	WiSi	StudyPoints
1	0.12	120	67.00	0.06	4	1	0.12	0.60
2	0.1	120	109.00	0.10	6	1	0.10	0.50
3	0.03	120	106.00	0.10	6	1	0.03	0.15
4	0.08	120	130.00	0.12	7	0	0.00	0.00
5	0.1	120	84.00	0.08	5	1	0.10	0.50
6	0.07	120	83.00	0.07	4	1	0.07	0.35
7	0.12	120	119.00	0.11	6	1	0.12	0.60
8	0.07	120	66.00	0.06	4	1	0.07	0.35
9	0.08	120	66.00	0.06	4	1	0.08	0.40
10	0.08	120	68.00	0.06	4	1	0.08	0.40
11	0.1	120	98.00	0.09	5	1	0.10	0.50
12	0.05	120	119.00	0.11	6	1	0.05	0.25
	1	1440	1,115.00	1.00	61	11	0.92	4.6

5.7.3 Personalized Learning Sequence Module

The personalized learning sequence is a list of lessons recommended to the learners for the purpose of remediating learning difficulty after failing the summative examination. The objective is to trim down the number of students who will fail the class after they are given enough time to study the lesson again, perform reinforcement and mastery and then repeat the summative examination. With a 30-70% rate of student failure, there is a need for Sirte University to solve this problem in an academic setting.

Table 5.9 is a two-level personalized learning sequence. Initially, all students took the summative examination. If they failed, the students would undergo personalization process. The live data of student ID 802592 was extracted from the database to illustrate how the system recommended personalized learning sequence. Initially, the student failed the first summative examination and the teacher activated his reinforcement process. The system then extracted the examination performance from the examination table, the study performance from the study table and the review performance from the review table. This populated Table 5.9.

The table is dynamically generated exclusively for one student and varies accordingly among learners. The recommended learning sequence for the first reinforcement level is $L_{10} \rightarrow L_{11} \rightarrow L_1 \rightarrow L_9 \rightarrow L_4 \rightarrow L_7 \rightarrow L_3$. Seven lessons were recommended which was a 41.66% decrease from the original 12 lessons. Unfortunately, the student failed again, producing a new learning sequence $L_1 \rightarrow L_4 \rightarrow$

$L_9 \rightarrow L_{10}$ which was a 42.8% decrease from the previous learning sequence. This was four lessons out of seven lessons. The student passed in the second reinforcement level. As observed, the number of lessons in each learning sequence was decreasing as reinforcement level was increasing. The sequence of the personalized learning was heuristic and acceptable since it gradually lessened the number of lesson in succeeding reinforcement process.

Table 5.9: Two- Level Personalized Learning Sequence

Lesson No	Percentage	Review Perf	Study Points	Weights	fv	Linear R	Linear Sequence	Cumulative Value	Random	Remarks	New Sequence
1	54.55	0.21	0.60	55.35	0.06	0.04	L10	0.04	0.93	Failed	**L10**
2	90.00	0.08	0.50	90.58	0.10	0.06	L11	0.10	0.40	Failed	**L11**
3	85.71	0.00	0.15	85.86	0.10	0.06	L1	0.16	0.21	Failed	**L1**
4	63.16	0.29	0.00	63.45	0.07	0.07	L9	0.23	0.84	Failed	**L9**
5	88.89	0.00	0.50	89.39	0.10	0.07	L4	0.31	0.56	Failed	**L4**
6	83.33	0.04	0.35	83.73	0.10	0.09	L12	0.40	0.31	Passed	
7	77.78	0.00	0.60	78.38	0.09	0.09	L7	0.48	0.85	Failed	**L7**
8	100.00	0.00	0.35	100.35	0.11	0.10	L6	0.58	0.31	Passed	
9	60.00	0.13	0.40	60.53	0.07	0.10	L3	0.68	0.99	Failed	**L3**
10	36.36	0.17	0.40	36.93	0.04	0.10	L5	0.78	0.04	Passed	
11	50.00	0.08	0.50	50.58	0.06	0.10	L2	0.89	0.21	Passed	
12	77.78	0.29	0.25	78.32	0.09	0.11	L8	1.00	0.93	Passed	
				873.45	1.00						

Lesson No	Percentage	Review Perf	Study Points	Weights	fv	Linear R	Linear Sequence	Cumulative Value	Random	Remarks	New Sequence
1	44.44	0.21	0.60	45.25	0.09	0.09	L1	0.09	0.61	Failed	**L1**
3	87.50	0.00	0.15	87.65	0.17	0.13	L4	0.22	0.62	Failed	**L4**
4	66.67	0.29	0.00	66.96	0.13	0.15	L7	0.36	0.28	Passed	
7	75.00	0.00	0.60	75.60	0.15	0.15	L9	0.52	0.52	Failed	**L9**
9	77.78	0.13	0.40	78.30	0.15	0.15	L10	0.67	0.78	Failed	**L10**
10	77.78	0.17	0.40	78.34	0.15	0.16	L11	0.83	0.35	Passed	
11	82.35	0.08	0.50	82.94	0.16	0.17	L3	1.00	0.39	Passed	
				515.04	1.00						

5.7.4 Reinforcement Process Module

Reinforcement process is giving additional learning activities as a penalty for not passing the first summative examination. However, this process aims to help students pass the course. Learning materials are presented in various media formats such as PDF, documents files, codes, executable files, videos, gif, and animations. The number of activities for reinforcement varies accordingly to different students due to the reinforcement rule-based mechanism incorporated in the system. The lower the fitness value, the more reinforcement activities are allotted to the learners. Usually, reinforcement learning is activated by the teacher for all students who wants to undergo additional learning and be given a chance to pass the course.

The personalized learning sequence produced in the previous section was activated, and in the process deactivating lesson not included in the selection process. Since roulette wheel algorithm was a selection process of the genetic algorithms, it was only natural that it inherited the heuristic properties of GA. Since the sequence was based on random numbers, there were instances that even lessons with very high competency level were retained for reinforcement. To compensate for such heuristic properties, the number of reinforcement of the fitness value which was higher than 80 is one or zero.

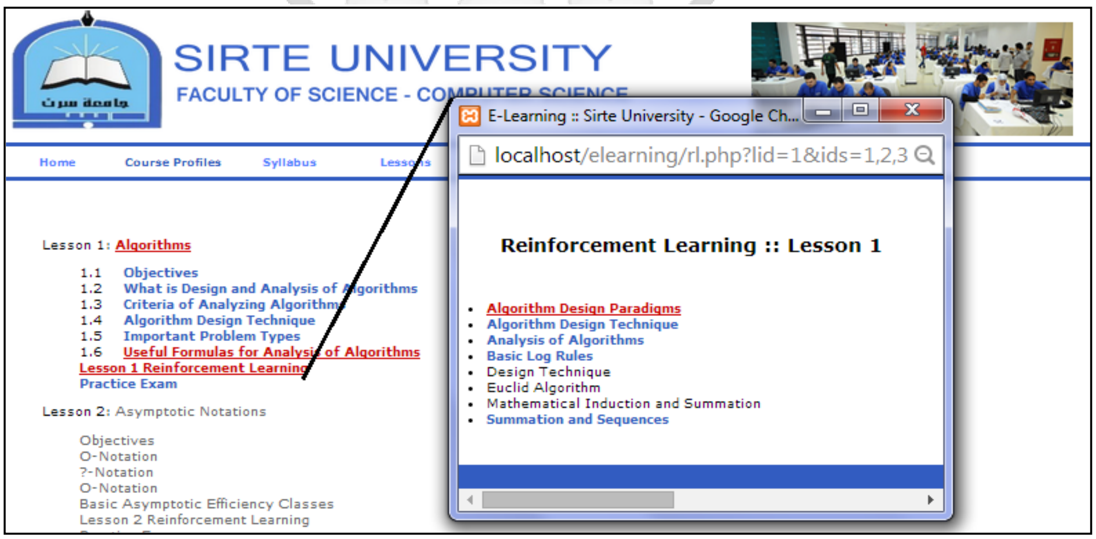


Figure 5.20: Reinforcement Process

Figure 5.20 is a live chunk of the reinforcement process. Base on the personalized learning sequence, lessons that were selected would be activated. As shown in the figure, L_1 was activated while L_2 was deactivated. Clicking the reinforcement learning link at the bottom of the lesson outline activated the reinforcement process. Blue colored links indicated the reinforcement files randomly selected for additional reading.

Students were not allowed to do summative examination without reading the materials since the system would record and monitor the reinforcement files. As shown on Figure 5.20, the total number of reinforcement files is five as reflected in the rule-based system based on the overall score or percentage of Lesson 1. To indicate that the student read the files, the system window of the reinforcement file could be closed unless all links which were originally in blue would turn red. This was necessary to enforce reading the materials.

5.8 Summary

This chapter shows that the implementation of the e-learning prototype is successful considering its design of assessment and content. This also includes learning instructions which had strongly been considered and ubiquitously examined. During the experiments, the system was able to recommend a personalized learning sequence by using the three performance indicators which produced a single numerical fitness value for each lesson. Various examinations with incorporated control mechanism provided a guarantee that reinforcement learning would occur. The system could load reinforcement files depending on the rule-based reinforcement system. The use of cumulative rewards and punishment was successfully handled by the reinforcement learning architecture.

Chapter 6: Discussion of Results

I was bold in the pursuit of knowledge, never fearing to follow truth and reason to whatever results they led, and bearding every authority which stood in their way.

Thomas Jefferson (1743 – 1826)

However beautiful the strategy, you should occasionally look at the results.

Sir Winston Churchill (1874 - 1965)

Somewhere, something incredible is waiting to be known.

Dr. Carl Sagan (1934 - 1996)

6.1 Introduction

This chapter presents the discussion of the results before and after the implementation of the reverse roulette wheel selection algorithms, mastery learning, and reinforcement learning. This is a case study conducted at Sirte University. This chapter discusses the summary of the demographic profiles of the students, the pre-survey results using Cronbach's alpha, the post survey acceptability of the prototype system's features and functionality, and the various experimental results which were derived from e-learning prototype. This also includes the discussion of the Bloom Cognitive assessment and its correlation to theme extraction using a special software called Semantria.

Some of the results presented in this section are structured and customized for discussion which can be verified in the appendices of this thesis or in the e-learning prototype. The extracted data in the different tables of the database were obtained dynamically during the learning process. In-depth analyses of the results are included to reflect the researcher's views, opinions and observations with which were strengthened and justified from the various scientific output and scholarly published materials. The discussion and analyses of the results are presented by answering research questions.

6.2 Respondents

Out of the 41 students surveyed, 38 returned the post survey questionnaires; six were males and 32 were females. There were twenty- eight fourth year students and 10 were in third year. These 10 students passed already the course prerequisite. The average age of the respondents was 23.2 years old with a standard deviation of 1.6. All the respondent owned electronic devices at home and had access to the Internet. Twenty (20) had personal computer, laptops and computer tabs while 10 had personal computers only, and eight had used laptop. Of the total respondents, 20 used WIFI using Wi-Max USB technology, 15 used MyDSL and three used RiFi internet connectivity.

Thirty-eight (38) respondents out of 41 returned the survey forms, and they were asked about their internet connectivity in the preliminary questions. Results show that 100% of the respondents have access to the internet via different mediums. The students were able to access the learning modules anywhere, anytime at their own convenience and time disposal. In Libya, this learning environment is convenient and acceptable especially among woman students, since they are preoccupied with household chores, married life, and with their traditions and cultures. With a ratio of 1:8 for male versus female students, the implementation of e-learning is an excellent opportunity to lessen the learning gap. Finishing college is not a priority among the male Libyan students because the Libyan government subsidizes almost everything. Libyans focus on doing business to earn money and prepare themselves for marriage. Libyan women on the other hand, take university education as a perfect opportunity to make themselves marketable to prospective husbands. Although this can be considered as a cultural set-up, the use of e-learning can lessen government spending, shorten the years of staying at the university, and increase the competency level of students.

6.3 Internal Consistency and Z-test Results

Prior to the post survey for students, the survey forms were presented among academic staff to validate the measurement scale and questionnaires. The Cronbach‘s Alpha coefficient for internal consistency reliability test was used for each scale. Cronbach‘s alpha reliability coefficient normally ranges between 0 and 1. George and Mallery (2003) provide the following rules of thumb: $\alpha \geq .9$ – Excellent, $.7 \leq \alpha < .9$ –

Good, .6 ≤ α < .7 – Acceptable, .5 ≤ α < .6 – Poor and α < .5 – Unacceptable. The results of Cronbach's Alpha coefficients for each scale are presented in Table 6.1.

Table 6.1: Cronbach's Alpha Coefficient for each Measurement Scale

VARIABLES	CRITERIA						
	Content	Visual Design	Accessibility	Assessment	Navigation	Learning Support	Interactivity
k	5	5	5	5	5	5	5
Cumulative Variance (Yi)	0.86	0.99	1.08	1.00	0.99	1.01	1.01
Variance	1.75	2.06	2.14	2.14	2.41	2.08	2.31
α (Alpha)	**0.63**	**0.65**	**0.62**	**0.67**	**0.74**	**0.64**	**0.70**

The results indicated that all scales satisfied the requirement for internal reliability. All Cronbach's alphas of the scales were higher than .60. The lowest value of Cronbach's alpha is .62 in Accessibility scale while the highest is .74 in Navigation scale. To determine how each question in the survey impacts the reliability, Cronbach's alpha can be calculated after deleting the *i*th variable for each $i \leq k$ as shown in Figure 6.1. Thus, for a test with k questions, each score x_j alpha is calculated for x_i for all i where $x_i = \sum_{j \neq i} x_j$.

The overall reliability for Content is .636 while individual reliability of questionnaire within the scale are: for C1 is .677, C2 is .774, C3 is .519, C4 is .337 and C5 is .457. In this scale, C4 was the most affected and could be deleted from the survey form. The Visual Design overall reliability is .650 and the most affected is V5 with Cronbach value of .457. On the other hand, Accessibility scale overall reliability is .617 and the most affected questions were A3 and A4 which both have values of .427. Similarly with the remaining scale, questions with smaller Cronbach's alpha compared to the overall scale reliability were the most affected and could be deleted from the survey form. If the reliability coefficient increases after an item is deleted, it can be assumed that the item is not highly correlated with the other items. Conversely, if the reliability coefficients decreases, it can be assumed that the item is highly correlated with the other items (Zaiontz, 2012). As can be seen in the table, the omission of any single question does not change the Cronbach's alpha very much. Questions with low reliability compared to its overall measurement scale were not deleted because small set of questionnaires affects the reliability value (Tavakol & Dennik, 2011). In this case, five questions in each measurable scale were acceptable and there was no need to delete the item since the uniqueness of each item could easily be seen. According to Cortina (1993), the uniqueness of the item is assessed with the coefficient alpha.

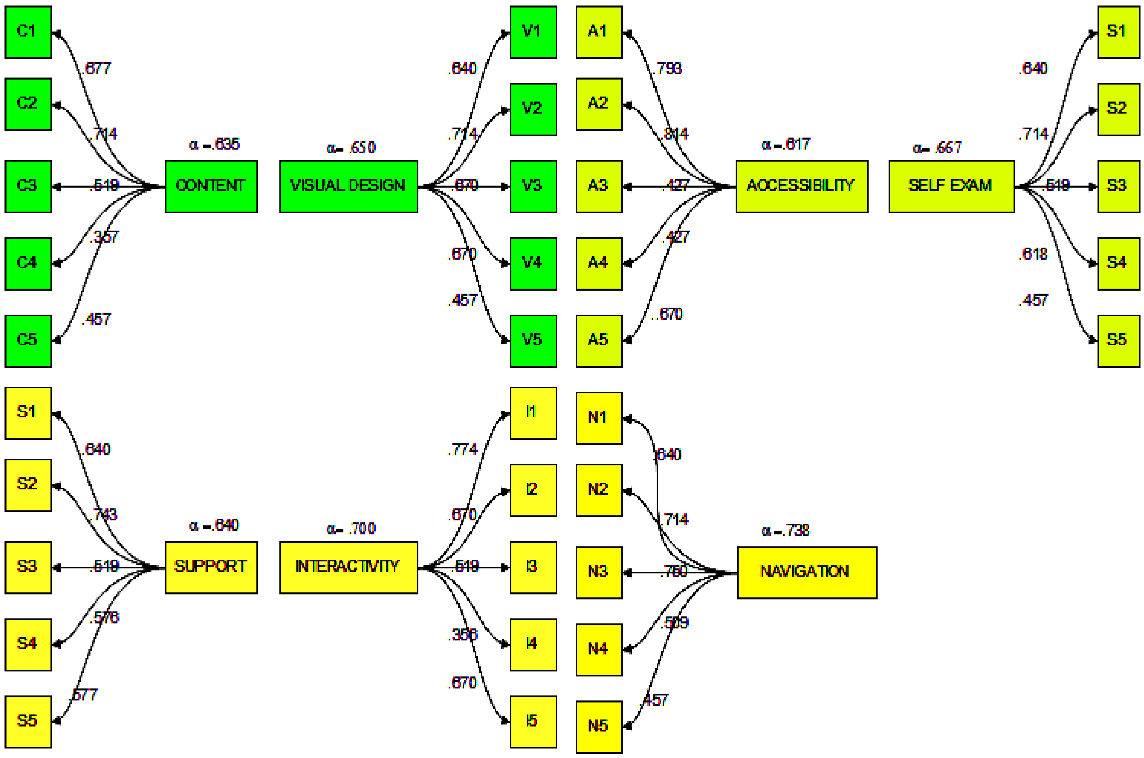


Figure 6.1: Reliability Coefficient after Deleting an Item

Table 6.2 shows the results of the post survey among staff members to determine the overall reliability of the software and the 280 questionnaires stored in the Item Bank which were used for various assessments employed in the prototype. During the survey, random questions were shown from the system to evaluate and rate their reliability. The overall internal consistency of the software is .81, which is considered good while the overall reliability for the 60 questionnaires for Bloom's Cognitive Taxonomy is .84. Similarly, the internal reliability for questionnaires which were used for formative and summative assessment is .72.

Table 6.2: Crobach's Reliability of Questionnaires and Overall Acceptability

	Software Acceptability	Bloom Taxonomy	Questionnaires
K	13.00	3.00	3.00
sum var	7.10	2.22	1.13
var	28.64	5.02	2.19
α= alpha	0.81	0.84	0.72

Alpha is an important concept in the evaluation of assessments and questionnaires and other measurement scale. It is mandatory that assessors and researchers should estimate this quantity to add validity and accuracy to the interpretation of their data. A low value of alpha can be attributed to a low number of questions, poor interrelatedness between items or heterogeneous constructs. For example, if a low alpha is due to poor correlation between items, then some items should be revised or discarded. If alpha is too high, it may suggest that some items are redundant as they test the same questions but in a different guise (Streiner, 2003). As observed in the study, the overall alpha is not too high but still considered highly acceptable at all levels.

Table 6.3: Z-test of Different Measurable Scale

Criteria	Mean	Standard Deviation	z
Content	4.37	0.79	2.89
Visual Design	4.29	0.69	2.57
Accessibility	4.26	0.76	2.13
Self Assessment	4.34	0.88	2.40
Navigation	4.21	0.62	2.09
Learning support	4.29	0.93	1.92
Interactivity	4.26	0.92	1.76
Motivation	4.29	0.80	2.22

Table 6.3 is the summary of the perception of students on the significant level of different measurable scales. The mean is given with its standard deviation. The highest mean is 4.37 from the Content scale while the lowest is 4.21 from Navigation scale. The *z*-values at $z_{:05}$ = 1:645, making all the critical values of measurable scale significant using one-tailed critical region. The z-values computed are greater than tabular value at alpha of .05. Therefore, the null hypothesis stated in section 3.6 is rejected in favor of

the alternative explanation that students agree with all the measurable scale of the prototype.

Based on Likert scale, the mean of each measurable variable is higher than the agreeable level which is successfully correlated by the *z*-test. Based on the results taken from the randomly selected sample, the null hypothesis is indeed false. According to Privatera (2014), the power in hypothesis testing is the probability of rejecting a false null hypothesis.

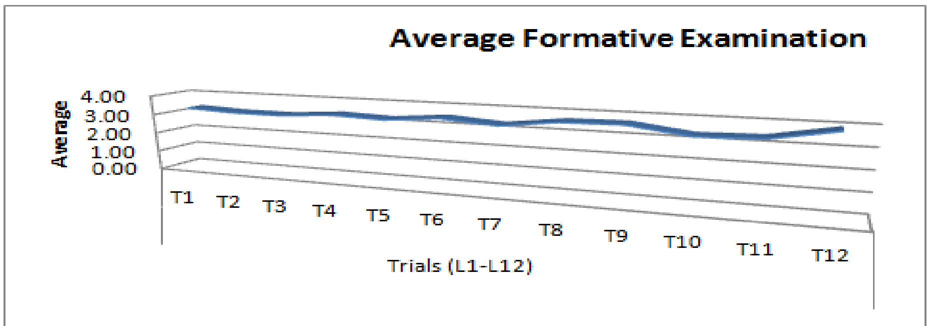
6.4 Experimental Results and Analysis

This section of the chapter focuses on the experimental results and its impact to the student performance. The discussion also includes the impact of formative assessment, the personalization process, and reinforcement learning to remediate learning difficulty. The later part of this section discusses the overall effect of these various mechanisms which contributed to the tangible learning benefits.

6.4.1 Formative Assessment

The purpose of formative assessments is to promote the attainment of knowledge by the students rather than testing a body of attained knowledge. Designing a curriculum that includes many rich formative assessments will result into a student-centered approach to teaching which often leads to students' success. To achieve this objective, the system employs a forced mechanism which prevented student from proceeding to the next learning materials without passing the formative assessment at hand. It is in this process that explanation facilities, lesson links, and re-loading of random questions occurred in the prototype. This flexibility allowed students to suit their knowledge and exert effort to pass every formative or practice administered. As the students went through the e-learning materials, several formative assessments were implemented. This allowed student to recognize and address any misconceptions or learning difficulty they had during the learning process.

Figure 6.2 shows the average number of time spent by the 41 students in taking the formative assessment for L_1 to L_{12}. The average trials for L_1, T_1 is 3.31 while L_{12} obtained the most number of trials with an overall average of 3.94. The students could reload as many times as they wanted the formative assessment. This allowed them to review the learning materials. The more trials were employed, the more students gained efficiency in taking a timed test in an online format. Preview questions were used to test their current knowledge and for them to be familiar with the questionnaire formats which were similar to the ones given during summative examinations. By conducting these trials, a student would understand which domains he/she was proficient and in which areas he/she would require additional study and preparation. Each offered questions which were randomly selected from the Item Bank. At the end of each set of eight questions, student would be able to see the scores, and give feedback on the answers.



	Trials (L1-L12)											
	T1	T2	T3	T4	T5	T6	T7	T8	T9	T10	T11	T12
Average	3.31	3.20	3.19	3.38	3.29	3.52	3.32	3.65	3.70	3.35	3.42	3.94

Figure 6.2: Average Number of Times in Taking Formative Assessment

	Practice Exams											
	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P11	P12
Average	6.97	7.17	6.83	7.10	7.03	7.11	7.04	6.92	7.16	6.96	7.11	6.96

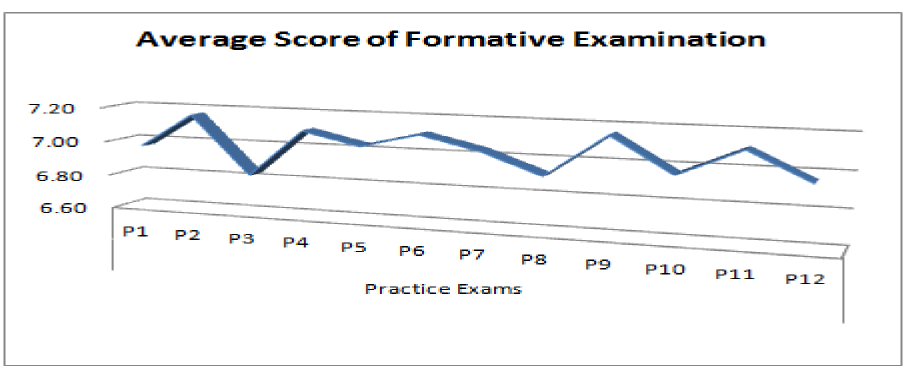


Figure 6.3: Average Score in Practice Examination

The graph in Figure 6.3 shows the average score of the class in taking practice or formative assessments. The highest overall average score P_2 is 7.17 for L_2 while P_3 with 6.83 for L_3 is the lowest. The e-learning prototype dictated that only 6 out of 8 score would be recorded in the database, forcing the student to study harder until a competency level was achieved. If the student failed the formative, he/needs to reload a new formative assessment. The trial table in figure 6.1 was updated every time a new formative was reloaded to a particular student.

The Item Bank contains over 280 questions and distributed across three examinations extracted from 12 different question types table. These questionnaires can test students' knowledge while the answers, explanations, and further reading links improved student's learning. Doing practice examination several times enabled students to systematically go through the Item Bank and allows them access to questions from all topics relevant to the current examination in a random pattern. These encouraged students to answer as many questions as possible, testing their knowledge on multiple topics. It followed the "practice makes perfect" attitude. The study of Walker, Brooks, Hammond, Fall, Peifer, Schnell and Schottel (2010), shows that a 4.3 and 5.7 percentage points overall is gained from practice examination. The results indicated that online practice significantly improved student learning and examination performance. Practice testing is more powerful, useful for learners of different ages and abilities. It is more far effective than summarization, highlighting keywords mnemonics, imagery, and rereading (Pinola, 2013). The results of the study show how students benefited from the prototype.

6.4.2 Bloom Taxonomy Assessment

The Bloom Cognitive Taxonomy is a special assessments that measures the cognitive development of the student while taking the e-learning course. This 60-items assessment was specifically designed based on the Cognitive Schema and readily extracted from the Item Bank database. The assessment was taken every four weeks during the experimental sessions. The assessment was equally divided to six categories specified in the Bloom Cognitive Taxonomy.

For a Bloom Cognitive Taxonomy to become effective, the examination must be entirely based on the use of all six levels of the pyramid as shown in Figure 2.7. For a student to evaluate his/her cognitive development he/she needs to *Remember* the basic facts. But beyond that, the student has to *Understand* the significance of those facts, and their interrelatedness, *Apply* them to solve real life problems, *Analyze* everything from all possible alternatives and study the results. After which the student has to *Evaluate* several alternatives or solutions and which of these is most reliable. He/She has to decide which of the several alternative answers is most appropriate in a particular case. Lastly, the student has to *Create* knowledge and experience from multiple sources into a high-order schema which will equip him/her to deal with the domain more effectively.

REMEMBER				UNDERSTAND				APPLICATION			
R1	R2	R3	R4	U1	U2	U3	U4	A1	A2	A3	A4
2.5	4.12	6.17	8.6	2.83	3.55	5.12	8.29	2.1	4.2	5.5	7.9

E1	E2	E3	E4	N1	N2	N3	N4	C1	C2	C3	C4
1.88	2.74	3.33	4.12	1.74	3.64	5.64	7.45	1.62	3.52	4.81	6.67
EVALUATE				ANALYZE				CREATE			

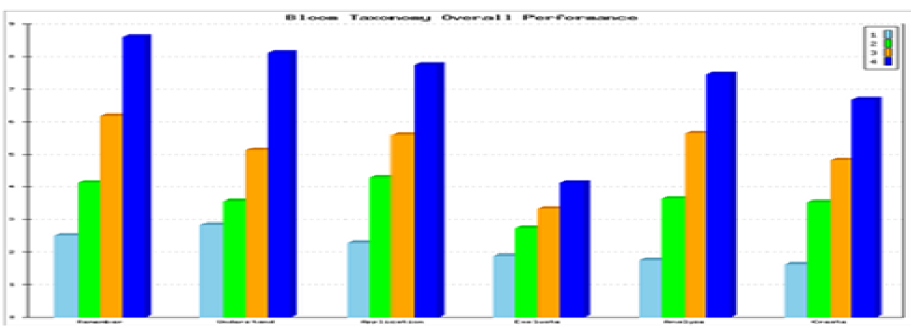


Figure 6.4: Average Cognitive Graph Output

The graph in Figure 6.4 shows the overall class average of the cognitive development of students taken every four weeks during the training. It must be noted that the cognitive level of the six categories increased. The *Remember* category, for example, had an initial average of 2.5 for R1, 4.12 for R2, 6.17 for R3 and 8.6 for R4. These initial scores clearly represent 25% of the R1 followed by an increase of 16% for R2, an increase of 20% for R3 and an increase*d* of 24.3% for R4. Similarly, as the other learning process or training neared its end, the individual average score increased. As further shown in the graph, the category with highest gain is *Remember* since it is the easiest among the six categories while *Evaluate* has the lowest learning gain. The purpose of this was to determine whether students would improve their learning by recalling lessons that they had read and understood as they went through the sessions. As a general observation and as shown in the graph, students increases their cognitive domain at different levels. However, these results cannot be interpreted as truly cognitive gain due to the absence of a single domain during testing. The questions were defined and extracted from various topics. To compensate for this gap, the study examined the cognitive development and its relationship to the experiences and perceptions of the students in using the prototype. The study employed Semantria, a special software that can compute and determine whether the coded transcripts of the student is positive, negative or neutral. During the post survey, the students were asked to write briefly their reactions, perceptions and experiences in using the system to correlate the results of the cognitive development. Out of the 38 students, 35 wrote their reactions, perceptions or experiences in the survey form. Their responses were coded and transformed into digital transcripts for further analysis.

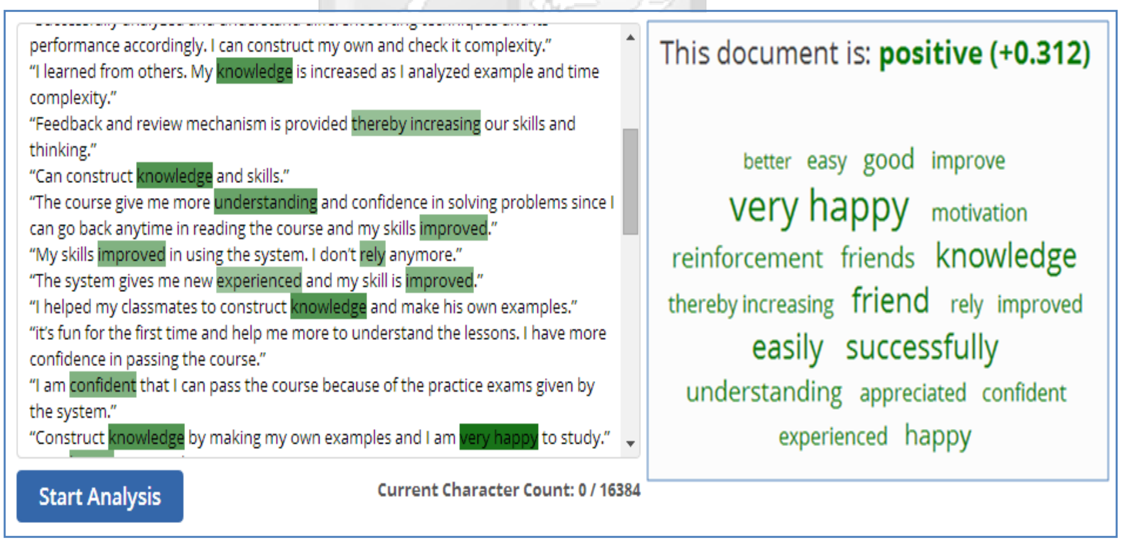
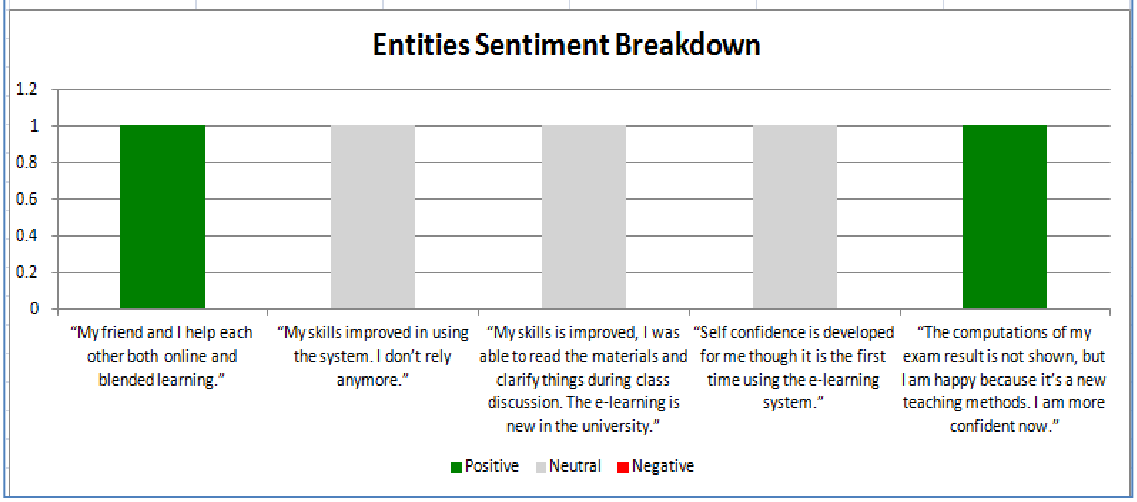


Figure 6.5: Semantria Analysis of the Digital Transcript

Figure 6.5 shows the output of the Semantria and revealed that the digital transcripts are positive with a score of +.321. Several positive words revealed the following words: *very happy, friends, motivate, improve, understanding, knowledge, and good.* According to Scheve (2014), students who have high cognitive benefits and self esteem will likewise reflect these in life or in their reactions to objects or surroundings. Being happy and positive increases the overall self-esteem and partly results to good school performance (Baumeister, Campbell, Krueger & Vohs, 2003). Thus, it can be concluded that the results coincide with the findings of Franken (1994) that being happy results to "making reasonable progress towards the realization of a goal".

Table 6.4: Entity Sentiment Breakdown of the Digital Transcripts

Entity	Entities Count	Entity Type	Positive Entities	Neutral Entities	Negative Entities
"My friend and I help	1	Quote	1	0	0
"My skills improved in	1	Quote	0	1	0
"My skills is improved,	1	Quote	0	1	0
"Self confidence is	1	Quote	0	1	0
"The computations of	1	Quote	1	0	0

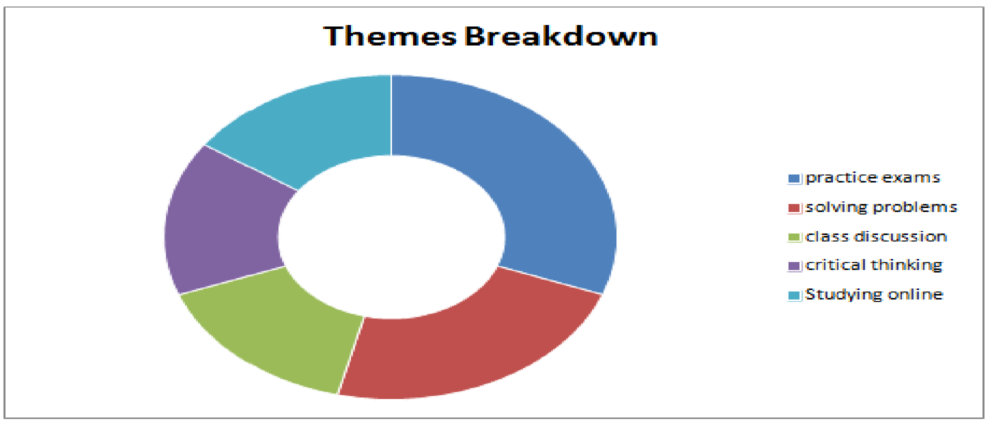


To further strengthen the findings, Semantria extracted five entities from digital transcripts and identified two positive sentiments and 3 neutral leading to positive. These results can be seen in Table 6.4. No negative feedback is received from the 35 coded entities. Sentiment analysis is the process of detecting positive, negative, or neutral feelings in a piece of writing (Pang & Lee, 2002). Semantria software is an information-gathering behavior that discovers what other people think (Turney, 2002).

Table 6.5 shows the five themes extracted from the digital transcript. They are *practice examinations, solving problems, class discussion, critical thinking*, and *study* *online* with their respective themes count of 4, 3, 2, 2, 2. The theme sentiment score is between – 1 and +1 is considered neutral. The overall theme sentiment polarity is neutral. However, according to Koppel and Schler (2006), neutral improves the overall accuracy and should not be considered as a state between positive and negative but as a separate class that denotes the lack of sentiment. The sentence "The weather is hot" for example, cannot be considered negative or positive.

Table 6.5: Themes Extracted from the Digital Transcript

Theme	Themes Count	Theme Sentiment Score	Theme Sentiment Polarity
practice exams	4	-0.00590241	neutral
solving problems	3	0.064992435	neutral
class discussion	2	0.313600004	neutral
critical thinking	2	0	neutral
Studying online	2	-0.057878751	neutral



6.4.3 Personalization Analysis

Personalized learning sequence or PLS is a lists of lessons recommended by the system to undergo reinforcement in order to remediate the learning difficulty. For the purpose of discussion, a partial list of student who went for reinforcement was extracted. Nevertheless, some of the properties observed were sufficient to make a generalized results.

Table 6.6 shows the 18 out of 27 students who underwent reinforcement process with their corresponding ID numbers and their various PLS. Initially at Level 0, all student read the materials at the sequence of $L_1 \rightarrow L_2 \rightarrow L_3 \rightarrow L_4 \rightarrow L_5 \rightarrow L_6 \rightarrow L_7 \rightarrow L_8 \rightarrow L_9 \rightarrow L_{10} \rightarrow L_{11} \rightarrow L_{12}$. After reading all the materials and successfully completing all the requirements enforced by the system, the student then took the first set of summative examination. Students who failed the summative examination, undergoes first level of reinforcement. Student ID 602164 was given a chance with a new sequence $L_6 \rightarrow L_3 \rightarrow L_{12} \rightarrow L_1 \rightarrow L_7 \rightarrow L_{11} \rightarrow L_4 \rightarrow L_{10} \rightarrow L_{2,}$. A total of 9 or 75% of lesson was recommended by the system and the student luckily passed after reinforcement. The case of student 602164 shows that regardless of the number of lessons recommended by the system, the student will still pass the course if given the chance. Many students passed the course undergoing the same process wherein after the reinforcement stage, rewards were given by allowing them to read again the reading materials. Another student ID 1102180 underwent reinforcement level 1 with the following personalized learning sequence: $L_{12} \rightarrow L_3 \rightarrow L_6 \rightarrow L_9 \rightarrow L_5 \rightarrow L_4 \rightarrow L_1$,. There was a decrease of 41% on the number of lessons to re-study. However, the student failed the second summative examination, forcing the system to recommend a new personalized learning sequence $L_5 \rightarrow L_1 \rightarrow L_{12}$. This is a 43% decrease on the number of lessons to re-study based on the previous learning sequence. The student passed after the second level of reinforcement, similarly with other learners but with different learning sequence. Notice that the proposed learning path or sequence can simultaneously consider both the curriculum difficulty level and the curriculum continuity of the successive curriculum while implementing the personalized learning sequence of the learning process. In this way, the system guaranteed that students would pass the e-learning course as it gradually eliminated the lesson in the curriculum vector while increasing the gap of passing the competency level.

The results are heuristic yet they guarantee that the new learning sequence becomes smaller as the process approaches the stop criterion. Being heuristic in nature, there is a minimal chance that a lesson with a very high fitness value will be selected. This mechanism is leveraged by the rule-based punishment system in the form of giving minimal reinforcement. Instead of recommending all the lessons which have failed, the system relies on the random numbers as filtering mechanism. Once a personalized learning sequence is recommended by the system, the students will be directed to undergo mastery and reinforcement process.

Table 6.6: Summary of Personalization Process

	Generation		
Stud_ID	No Reinforcement (Level 0)	Personalized Learning Sequence Level 1	Personalized Learning Sequence Level 2
802092	$L_1 \rightarrow L_2 \rightarrow L_3 \rightarrow L_4 \rightarrow L_5 \rightarrow L_6 \rightarrow L_7 \rightarrow L_8 \rightarrow L_9 \rightarrow L_{10} \rightarrow L_{11} \rightarrow L_{12}$	$L_4 \rightarrow L_1 \rightarrow L_3 \rightarrow L_5 \rightarrow L_9 \rightarrow L_{10} \rightarrow L_2 \rightarrow L_8$	
802137	$L_1 \rightarrow L_2 \rightarrow L_3 \rightarrow L_4 \rightarrow L_5 \rightarrow L_6 \rightarrow L_7 \rightarrow L_8 \rightarrow L_9 \rightarrow L_{10} \rightarrow L_{11} \rightarrow L_{12}$	$L_6 \rightarrow L_1 \rightarrow L_4 \rightarrow L_{10} \rightarrow L_{12}$	$L_6 \rightarrow L_{12} \rightarrow L_1$
802151	$L_1 \rightarrow L_2 \rightarrow L_3 \rightarrow L_4 \rightarrow L_5 \rightarrow L_6 \rightarrow L_7 \rightarrow L_8 \rightarrow L_9 \rightarrow L_{10} \rightarrow L_{11} \rightarrow L_{12}$	$L_{12} \rightarrow L_4 \rightarrow L_9 \rightarrow L_{11} \rightarrow L_{10} \rightarrow L_3$	$L_{12} \rightarrow L_4$
802197	$L_1 \rightarrow L_2 \rightarrow L_3 \rightarrow L_4 \rightarrow L_5 \rightarrow L_6 \rightarrow L_7 \rightarrow L_8 \rightarrow L_9 \rightarrow L_{10} \rightarrow L_{11} \rightarrow L_{12}$	$L_7 \rightarrow L_9 \rightarrow L_4 \rightarrow L_{12} \rightarrow L_2 \rightarrow L_8 \rightarrow L_5$	$L_{12} \rightarrow L_9 \rightarrow L_2 \rightarrow L_4$
802236	$L_1 \rightarrow L_2 \rightarrow L_3 \rightarrow L_4 \rightarrow L_5 \rightarrow L_6 \rightarrow L_7 \rightarrow L_8 \rightarrow L_9 \rightarrow L_{10} \rightarrow L_{11} \rightarrow L_{12}$	$L_{12} \rightarrow L_1 \rightarrow L_6 \rightarrow L_2 \rightarrow L_{11} \rightarrow L_7 \rightarrow L_{10} \rightarrow L_4 \rightarrow L_8 \rightarrow L_5$	$L_{12} \rightarrow L_{11} \rightarrow L_{10} \rightarrow L_1 \rightarrow L_4 \rightarrow L_5$
802491	$L_1 \rightarrow L_2 \rightarrow L_3 \rightarrow L_4 \rightarrow L_5 \rightarrow L_6 \rightarrow L_7 \rightarrow L_8 \rightarrow L_9 \rightarrow L_{10} \rightarrow L_{11} \rightarrow L_{12}$	$L_3 \rightarrow L_4 \rightarrow L_2 \rightarrow L_1 \rightarrow L_7$	$L_2 \rightarrow L_1$
802513	$L_1 \rightarrow L_2 \rightarrow L_3 \rightarrow L_4 \rightarrow L_5 \rightarrow L_6 \rightarrow L_7 \rightarrow L_8 \rightarrow L_9 \rightarrow L_{10} \rightarrow L_{11} \rightarrow L_{12}$	$L_6 \rightarrow L_9 \rightarrow L_4 \rightarrow L_{11} \rightarrow L_2$	$L_{11} \rightarrow L_2$
1002043	$L_1 \rightarrow L_2 \rightarrow L_3 \rightarrow L_4 \rightarrow L_5 \rightarrow L_6 \rightarrow L_7 \rightarrow L_8 \rightarrow L_9 \rightarrow L_{10} \rightarrow L_{11} \rightarrow L_{12}$	$L_4 \rightarrow L_6 \rightarrow L_{12} \rightarrow L_8$	
1002045	$L_1 \rightarrow L_2 \rightarrow L_3 \rightarrow L_4 \rightarrow L_5 \rightarrow L_6 \rightarrow L_7 \rightarrow L_8 \rightarrow L_9 \rightarrow L_{10} \rightarrow L_{11} \rightarrow L_{12}$	$L_{12} \rightarrow L_1 \rightarrow L_6 \rightarrow L_8 \rightarrow L_{11} \rightarrow L_5$	$L_{12} \rightarrow L_8 \rightarrow L_{11}$
602164	$L_1 \rightarrow L_2 \rightarrow L_3 \rightarrow L_4 \rightarrow L_5 \rightarrow L_6 \rightarrow L_7 \rightarrow L_8 \rightarrow L_9 \rightarrow L_{10} \rightarrow L_{11} \rightarrow L_{12}$	$L_6 \rightarrow L_3 \rightarrow L_{12} \rightarrow L_1 \rightarrow L_7 \rightarrow L_{11} \rightarrow L_4 \rightarrow L_{10} \rightarrow L_2$	
802092	$L_1 \rightarrow L_2 \rightarrow L_3 \rightarrow L_4 \rightarrow L_5 \rightarrow L_6 \rightarrow L_7 \rightarrow L_8 \rightarrow L_9 \rightarrow L_{10} \rightarrow L_{11} \rightarrow L_{12}$	$L_{12} \rightarrow L_1 \rightarrow L_5 \rightarrow L_4 \rightarrow L_8 \rightarrow L_{10} \rightarrow L_2$	$L_{12} \rightarrow L_1 \rightarrow L_4 \rightarrow L_2$
802141	$L_1 \rightarrow L_2 \rightarrow L_3 \rightarrow L_4 \rightarrow L_5 \rightarrow L_6 \rightarrow L_7 \rightarrow L_8 \rightarrow L_9 \rightarrow L_{10} \rightarrow L_{11} \rightarrow L_{12}$	$L_1 \rightarrow L_9 \rightarrow L_3 \rightarrow L_{10}$	
802245	$L_1 \rightarrow L_2 \rightarrow L_3 \rightarrow L_4 \rightarrow L_5 \rightarrow L_6 \rightarrow L_7 \rightarrow L_8 \rightarrow L_9 \rightarrow L_{10} \rightarrow L_{11} \rightarrow L_{12}$	$L_{12} \rightarrow L_3 \rightarrow L_{11} \rightarrow L_7$	$L_3 \rightarrow L_{11}$
802487	$L_1 \rightarrow L_2 \rightarrow L_3 \rightarrow L_4 \rightarrow L_5 \rightarrow L_6 \rightarrow L_7 \rightarrow L_8 \rightarrow L_9 \rightarrow L_{10} \rightarrow L_{11} \rightarrow L_{12}$	$L_8 \rightarrow L_{11} \rightarrow L_{12} \rightarrow L_4 \rightarrow L_1 \rightarrow L_3$	$L_1 \rightarrow L_{12} \rightarrow L_3 \rightarrow L_{11}$
802592	$L_1 \rightarrow L_2 \rightarrow L_3 \rightarrow L_4 \rightarrow L_5 \rightarrow L_6 \rightarrow L_7 \rightarrow L_8 \rightarrow L_9 \rightarrow L_{10} \rightarrow L_{11} \rightarrow L_{12}$	$L_{10} \rightarrow L_{11} \rightarrow L_1 \rightarrow L_9 \rightarrow L_4 \rightarrow L_7 \rightarrow L_3$	$L_1 \rightarrow L_4 \rightarrow L_9 \rightarrow L_{10}$
902158	$L_1 \rightarrow L_2 \rightarrow L_3 \rightarrow L_4 \rightarrow L_5 \rightarrow L_6 \rightarrow L_7 \rightarrow L_8 \rightarrow L_9 \rightarrow L_{10} \rightarrow L_{11} \rightarrow L_{12}$	$L_{10} \rightarrow L_1 \rightarrow L_6 \rightarrow L_{11} \rightarrow L_{12} \rightarrow L_2 \rightarrow L_3$	$L_2 \rightarrow L_{12} \rightarrow L_3 \rightarrow L_1$
1102180	$L_1 \rightarrow L_2 \rightarrow L_3 \rightarrow L_4 \rightarrow L_5 \rightarrow L_6 \rightarrow L_7 \rightarrow L_8 \rightarrow L_9 \rightarrow L_{10} \rightarrow L_{11} \rightarrow L_{12}$	$L_{12} \rightarrow L_3 \rightarrow L_6 \rightarrow L_9 \rightarrow L_5 \rightarrow L_4 \rightarrow L_1$	$L_5 \rightarrow L_1 \rightarrow L_{12}$
1102182	$L_1 \rightarrow L_2 \rightarrow L_3 \rightarrow L_4 \rightarrow L_5 \rightarrow L_6 \rightarrow L_7 \rightarrow L_8 \rightarrow L_9 \rightarrow L_{10} \rightarrow L_{11} \rightarrow L_{12}$	$L_8 \rightarrow L_3 \rightarrow L_6 \rightarrow L_1 \rightarrow L_2$	

6.4.4 Reinforcement Analysis

Reinforcement process refers to the overall learning activities that remediate learning difficulty after failing the summative examination. This mechanism is immediately activated for a student who will be given a chance to re-study the learning materials. The lesser the fitness value, the lower the reinforcement process as recommended by the rule-based reinforcement mechanism incorporated in the system.

Table 6.7 shows the various reinforcement statistics accumulated by the students before passing the course. Thirty (30) additional files with different formats were given to student 602164. The student was also administered reinforcement level 1, 72 corrective activities, with 9 formative assessment or trials with an average of 6.67 and with a total rewards of 3.56. On the other hand, student 1102180, received 17 number of files, reinforcement level 2, 80 corrective activities, 10 number of trials for formative assessment and has an average of 7.17 and with a total reward points of 5.43.

Table 6.7: Summary of Reinforcement Process

Stud_ID	Number of Reinforcements	Reinforcement Level	Correctives Item	No. of Trials	Average Score	Rewards
802092	32	1	64	10	6.75	4.78
802137	16	2	64	8	7.33	4.98
802151	8	2	64	8	6.92	6.42
802197	11	2	88	11	6.42	4.88
802236	25	2	128	16	7.17	3.63
802491	9	2	56	7	6.92	5.02
802513	7	2	56	7	6.58	5.38
1002043	21	1	32	4	6.92	5.63
1002045	13	2	72	9	7.17	5.03
602164	30	1	72	9	6.67	3.56
8020920	14	2	88	11	7.58	5.18
802141	13	1	32	4	7.08	4.21
802245	7	2	48	6	6.83	5.31
802487	12	2	80	10	7.17	5.43
802592	12	2	88	11	7.00	5.89
902158	13	2	88	11	7.08	5.22
1102180	17	2	80	10	7.17	5.43
1102182	1	1	40	5	7.17	4.59

Reinforcement is among the many psychological tools that are used for teaching students. The two main kinds of reinforcement include, negative and positive reinforcement. Negative reinforcement attempts to enhance the learning process by eliminating or remediating learning difficulty (employing corrective measures). Positive reinforcement on the other hand, works by rewarding students based on their effort. Positive reinforcement is used for motivating students. Giving rewards to students who attain certain competency level will motivate them to study better, and increase their participation and effectiveness. Student who are acknowledged for their good work in their studies are more likely to succeed (Pink, 2011).

6.5 Learning Gains

The results based on the implementation of the prototype that incorporated the PLS and RL are considered successful. Table 6.8 shows that among the 41 students surveyed, 14 or 34% passed the course without reinforcement process. This means that 66% of the students failed the course. Out of the 27 students, 10 or 25% passed the course after reinforcement level 1 while 17 or 41% underwent reinforcement level 2.

Out of these 17 students, five or 12% failed the course. After all the reinforcements were administered, 22 student passed the course which is 54% of the total number of students studied. This achievement can be attributed to practice examination, personalized learning sequence and reinforcement process. From 14 students or 34% of the total number who passed the course without reinforcement, an additional 22 students or 54% passed the course after reinforcement. This is a total of 36 students or 88% who achieved competency level. The remaining five students or 12% of the total number discontinued the learning process for various and personal reasons.

Table 6.8: Overall Benefits of PLS and Reinforcement

	Reinforcement			Failed After Reinforcements
	Level 0	Level 1	Level 2	Level 1 and Level 2
Students	14	10	12	5
Percentage	34% (14)	25%	29%	12% (5)
Passed After Reinforcemnts		54% (22)		
Total Student Passed	88% (36)			

The results of the study can greatly help improve the teaching environment of Sirte University. With the implementation, the rate of students passing the course will increase and this increase will be guaranteed in the years to come. This will lead to an increase in the number of graduates of the University, decrease in the number of years of residency of the students and reduction of financial support by the government to the University.

Chapter 7: Summary and Conclusion

I hope that posterity will judge me kindly, not only as to the things which I have explained, but also to those which I have intentionally omitted so as to leave to others the pleasure of discovery.

Rene Descartes (1596 - 1650)

I think and think for months and years. Ninety-nine times, the conclusion is false. The hundredth time I am right.

Albert Einstein(1879 - 1955)

I pass with relief from the tossing sea of Cause and Theory to the firm ground of Result and Fact.

Winston Churchill (1974 – 1965)

Many researchers in the field of personalized learning or topic sequencing have proposed and implemented various mechanisms to improve the learning process with the main objective of maximizing learning and dynamically selecting the closest teaching operation to achieve the learning goals. However, despite recommending a personalized learning sequence, e-learning instructional strategists have failed to perform or address corrective measures to remediate learning misconceptions or learning difficulties immediately. Based on related literatures, these previous studies show that a number of e-learning materials are algorithmically expensive and complex due to various considerations. These include data extraction, involvement of complex functions, multi-processes or multiple stages, and issues of biases and correctness of the personalized learning sequence.

As e-learning or on-line learning materials continue to evolve and increase tremendously in educational setting, it is inevitable that an alternative, more realistic, simpler and a timely multi-based performance for a personalized learning sequence technique should be developed and implemented in the e-learning system. Additionally, this research combined the concepts of reinforcement learning and mastery learning in the areas of artificial intelligence and educational psychology respectively to remediate learning difficulty and improve learning output. The process of personalization, and reinforcement learning and how these concepts work and improve the learning process was demonstrated using an actual working prototype.

A. Preliminary Data

Many rigorous processes were undertaken to come up with e-learning system prototype. These included the content of the 12 lessons which had 65 subsections, twenty four (24) interactive MHTML files, seven (7) embedded videos, fourteen (14) simulations, twenty two (22) PowerPoint, forty five (45) PDF files, twenty two (22) word files, sixteen (16) executable files, sixteen (16) C++ source codes, two (2) simulated excel files, and 94 reference materials which were directly linked to the internet for additional reading. The design of 280 questions distributed among 12 question types, designed according to Bloom questions schema which were stored in the Item Bank database with different difficulty level. These were used for various assessments such as diagnostic, formative, and summative examinations. The content of the e-learning materials and the questionnaires in the Item Bank database was subjected to internal consistency and reliability test. This generally resulted to an acceptable level of Cronbach's alpha. Likewise, the overall features of the system in different measurable scale are generally significant at all levels.

There are many possible benefits of using the system if this is successfully implemented. It presents a personalized learning sequence to lessen the learning procedure. It also provides mastery and reinforcement learning as motivational factors and corrective measures and it can increase cognition and acquisition of knowledge. The system also provides pedagogical alternatives. Moreover, it can be seen as one of the possible solutions to many political, cultural and social problems in academic institutions in Libya. Politically speaking, during the war or declared holidays, students were not be able to attend universities due to restricted mobility brought by threats to security and safety. Culturally speaking, majority of the students in the university are women who are basically busy with family commitments and have no time to attend classes. Socially speaking, there is a communication barrier between foreign instructors who are tasked to deliver information technology education and the Libyan students. This is brought by almost two decades of English embargo. Thus, e-learning can fill these gaps by allowing students to personalize their course learning materials and study anywhere in their own time and disposal.

B. Results Contributions and Research Innovations

In this study, two major contributions were successfully demonstrated and implemented in the field of e-learning. These are the development of the improved version of RWSA called reversed roulette wheel selection algorithms that personalized learning sequence; and the implementation of reinforcement and mastery learning in the area of artificial intelligence and educational psychology.

The system successfully demonstrated the performance of reversed RWSA. The reversed roulette wheel selection algorithm is an improved version of a typical RWSA with linear ranking selection to lessen the bias in selection process and to perform elimination of the population in reversed manner. The algorithm computed the fitness function of all lessons and summed up the three performance indicators such as *study, examination, a*nd *review matrix*, to produce a single numerical value. The algorithm sorted and ranked accordingly the population according to its fitness. The fitness assigned to each individual depended only on its position in the individual rank and not on the actual fitness values. The ranking was linear so that it would eliminate or overcome the scaling bias or problem of a typical roulette wheel selection algorithm. The bias was the stagnations in cases where selective pressure was too small or there was premature convergence. The selection had caused the search to narrow down too quickly. Ranking introduced a uniform scaling across the population and provided a simple and effective way of controlling the selective pressure. The system normalized the fitness function until it converged into 1. The normalized fitness was compared to random number G(0,1) generated by the system and eliminated individual with high fitness values. Reversed RWSA mechanisms selected individuals with less than accumulated normalized values so that lessons with lower probability would be selected for recombination process and would be subjected to reinforcement process. Lessons with lower probability compared to cumulative value, indicated a presence of learning difficulty, misconceptions or low competency, level and therefore needed to undergo reinforcement process.

Several equations and mathematical conditions were formulated to produce the fitness function. The computation and population of different tables in the database were successfully simulated and implemented in the system. The fitness function is a particular type of objective function that is used to summarize, as a single figure of merit, how close a given design solution is in achieving the set aims. Normally, after each round of testing or simulation, the idea is to delete the 'n' as the best performing and retain worst in the population. The new 'n' undergoes mastery and reinforcement as a new breed from the design solutions. In designing the fitness function of the proposed system, the fitness function was mutable, as in niche differentiation or co-evolving the set of test cases. Computing the fitness function of the reverse roulette wheel selection algorithm depended strongly on three performance parameters that were formulated: *examination performance*, *study performance,* and *review performance* of the learner. Examination results were the direct information about a student's knowledge. The *examination performance* was dynamically constructed based on the student's background in reading the learning materials. Questions were provided to cover the topics which were most recently completed. Each question had a level of difficulty; answering correctly a harder question demonstrated a higher ability than correctly answering an easier question. *Study performance* on the other hand, refers to the main interaction that the students have with the learning environment through viewing or listening to the course materials in multimedia forms. The study performance was used to judge how much comprehension the student has gained through these activities while the *review topics performance* score on a topic recorded how many times the student had returned to review the topic again. It was based on how many times the topic was reviewed and how much the materials were viewed each time.

The system successfully implemented the process of how to produce a personalized learning sequence or PLS. The PLS are lists of lessons recommended by the system to students who need to undergo reinforcement to remediate learning difficulty. The results were dynamic and heuristic since it inherited the property of GA. The proposed learning path or sequence could simultaneously consider*s* the curriculum difficulty level and the curriculum continuity of successive curriculum while implementing personalized learning sequence in the learning process. In this way, the system guaranteed that students would pass the e-learning course as it gradually eliminated number of lesson while narrowing the gap of not passing or getting a certain competency level. Although the results were heuristic and dynamic, the PLS guaranteed that the new learning sequence became smaller as the process approached the stop criterion. Being heuristic in nature, there was a minimal chance that a lesson with very high fitness value was selected.

The prototype successfully demonstrated the reinforcement process. Reinforcement process refers to the overall learning activities that remediate learning difficulty after students fail the summative examination. This mechanism is immediately activated for student who will be given a chance to re-study the learning materials. The lesser the fitness value, the lower the reinforcement process is recommended by the rule-based reinforcement mechanism incorporated in the system. The system employed 60 rules to govern the reinforcement process and allowed two reinforcement levels. Additional files or corrective activities were dynamically and randomly selected based on the summative score. The maximum rewards were 10 points and were readily extracted from the study and review performance tables in the database.

Based on the results, the implementation of the prototype that was incorporated in the reversed-RWSA, PLS and RL is successful. The result is a convincing 54% increase of the passing rate as revealed in the case study. There are many factors that contributed to the success of the study. The prototype employed several controlling mechanisms during formative examination, summative examination, and in the Bloom's cognitive examination not to mention the use of different media formats that encouraged and increased motivation. During formative examination, students were able to review the question in multiple ways. This included, looking at explanation facilities, opening the link that points to specific part of the lesson, viewing the answers, and getting familiar with all the question types. During summative examination, students could view their different performance indicators while in the Bloom Cognitive examination, students could view and analyze their individual performance, thereby motivating them to continue learning. During reinforcement, it was proven that additional materials and corrective activities inevitably contributed to the overall results.

Another novel and convincing result is the correlation of the feedback of students and their academic performance. Individual response of student in the survey which reflected their perceptions and experiences in using the system is coded to produce digital transcripts. The digital transcripts were subjected to document content and theme extraction analyses. The overall analysis of the digital transcripts or documents is positive. The positive document score, document sentiment analysis and the theme extraction process correlated with the increase rate of student performance.

With these results, the implementation of this new prototype will greatly help in phasing out or gradually eliminating several academic problems faced by Sirte University. With the help of the e-learning implementation, the increase of the number of student passing the course is guaranteed, thereby reducing the length of residency of the students in the University. It can also solve academic problems brought by politics, security issues, cultures, and traditions since students can study anywhere and whenever online learning is possible.

C. Futures Works

The study is conducted for one semester using Algorithm Design course. The learning gains presented and the results does not provide a generalized learning benefits, therefore, a more experimental test and study should be conducted. For example, there is a need to have a control and experimental group to validate and compare the group's academic performance and learning gains. There is a need to implement this in a wider scale to demonstrate and encourage the stakeholders to realize the benefits of employing e-learning system in the university. Another future of the study is to implement in multi-university level to grasp the learning need of students in multi-sectoral level. Based on designing the questionnaires using the Bloom Cognitive Taxonomy, it must be implemented both specific-domain and scattered-domain to measure the cognitive development of the students in a deeper sense of cognitive learning. In terms of the performance matrix and data collection of students' prior knowledge, more variable is needed to address students' heterogeneity, and a need more intelligent profiling system to enhance learning delivery and increase learning benefits. Another study to be implemented is the use of a socially oriented e-learning to support online collaboration, online blended learning, group knowledge sharing, and knowledge construction which hypothetically improves the learning process and eventually lead to a very high academic performance.

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Appendix A: Research Questionnaires for Staff

Sirte University
Faculty of Science
Department of Computer Science

RESEARCH QUESTIONNAIRES
(for Staff/Faculty Members)

Roulette Wheel Selection Algorithms (RWSA) and Reinforcement Learning (RL) for Personalizing and Improving E-learning System

Confidentiality/Non-Disclosure Assurance

- My research on e-learning development and implementation focused in Libyan setting and is specifically conducted at Sirte University. The overall purpose of the research is to help students excel academically and outperform independently traditional learning using revolutionary technique in experimental way. The results will be presented as insights to the university for further study and adaptation of the new educational platform.
- The data and/or information collected shall be treated with utmost confidence and shall not be shared without prior permission from the respondents.

Research Objectives

- To collect personal data among staff and establish respondents' overall information.
- To determine the internal content reliability of the survey and questions stored both in the Lesson Item Bank and Bloom Taxonomy Item Bank.
- To determine the overall acceptability of the prototype using the criteria set by ISO 1926 standard.

Directions in Responding to the Questionnaires:

- Please check (√) the box that corresponds to each question. If you want to change your answer, put an X in the previous answer and check a new box that correspond to your new answer.

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PART A: YOUR PERSONAL DATA

A1. Staff Name: (Optional) ____________

A2. Position: ____________

A3. Gender: Male: ☐ Female: ☐

A4. Position: Technical Staff: ☐ Academic Staff: ☐ Managerial Staff: ☐

PART B: FEATURES and FUNCTIONALITY PARAMETERS of the E-LEARNING PROTOTYPE

This area will give us feedback whether the criteria and its content are relevant to be presented as evaluation tools for the students during system implementation. Applying Cronbach alpha analysis to determine its internal consistency and validity, kindly evaluate the following features in each criteria, honestly as you can.

CRITERIA	Disagree (0)	Agree (1)
B1: CONTENT OF THE COURSE		
Vocabulary and terminology used are appropriate .	☐	☐
Abstract concepts are illustrated with concrete examples.	☐	☐
Course handouts and printing of learning materials are allowed.	☐	☐
Presentation, videos, images, figures, tables and other media for illustrative materials are included.	☐	☐
Reference materials and web guides are included.	☐	☐
B2: VISUAL DESIGN		
Fonts (style, color and saturation) are easy to read.	☐	☐
Contrast – differentiate important elements to draw eyes	☐	☐
Repetition – internal consistency of design templates	☐	☐
Alignment – design and grid (horizontal/vertical aspects)	☐	☐
Visual Impact, neutrality. Proximity and influence to mental model.	☐	☐
B3: ACCESSIBILITY		
The course is free from technical problems (hyperlink errors and programming errors).	☐	☐
Course materials are available both online (internet based) and offline (Intranet based).	☐	☐

It can run in different browser and OS platform.	☐	☐
It provides printed materials for personal use (without pedagogical conflict).	☐	☐
Exam and assessment are available online and offline (equal opportunities).	☐	☐
B4: SELF ASSESSMENT		
Learners can start and locate the course, register and access starting page.	☐	☐
The course provides practice exam and feedback mechanism.	☐	☐
It provides grades and other performance matrix analysis.	☐	☐
It encourage self learning and is automatically adjusted to learner's level.	☐	☐
It has final assessment and exam	☐	☐
B5: NAVIGATION		
Learners always know where they are in the course.	☐	☐
The course allows learner to leave whenever they desire to but they can easily return to the closest logical point in the course.	☐	☐
Menus and navigational panel are readily available.	☐	☐
It discourages multiple open windows and overloaded pop-up reminders.	☐	☐
It provides direction to provide navigational problem.	☐	☐
B6: LEARNING SUPPORT		
The course offers tools that support learning.	☐	☐
The course includes activities both individual-based and group-based.	☐	☐
It provides additional learning materials.	☐	☐
It provides helps and explanation.	☐	☐
It allows social network media to facilitate collaboration and social aspect of learning.	☐	☐
B7: INTERACTIVITY		
The courses use games, simulations and case studies to gain attention and maintain motivation.	☐	☐
It allows "learning by doing" (playing and feeling involved).	☐	☐
Learners can find the activity useful in learning the materials.	☐	☐
It provides simulations and visualization tools to help students understand the materials.	☐	☐

It provides collaborative interactivity (communications with other learners such as video conferencing, virtual help and etc).	☐	☐

PART C: SOFTWARE OVERALL ACCEPTABILITY

This area of the survey reflects the overall quality and acceptability of the e-learning prototype adapted from ISO 9126 standard. Applying Likert Scale of 1 to 5, kindly evaluate the following criteria, as honestly as you can by checking (√) the corresponding box of your choice.

CRITERIA	1 Strongly Disagree	2 Disagree	3 Neutral	4 Agree	5 Strongly Agree
Accuracy of the content of the course materials.	☐	☐	☐	☐	☐
Compliance of the learning materials according to the Quality Assurance Office (objectives and learning outcomes)	☐	☐	☐	☐	☐
Security (Log-in mechanism, and data protection).	☐	☐	☐	☐	☐
Fault Tolerance (continuance of the system in the presence of unexpected errors)	☐	☐	☐	☐	☐
Recoverability (returning to normal operation in the occurrence of system failure)	☐	☐	☐	☐	☐
Understandability (coherence, clearness and readability)	☐	☐	☐	☐	☐
Learnability (allowing user to independently navigate the e-learning prototype and learn over time)	☐	☐	☐	☐	☐
Operability (software can run in different platform or the availability of alternative learning materials)	☐	☐	☐	☐	☐
Competitive performance (allowing student data and their respective records for personal evaluation)	☐	☐	☐	☐	☐
Ability to accomplish or read the materials in reasonable time and effort.	☐	☐	☐	☐	☐
Changeability (content can be modified and updated)	☐	☐	☐	☐	☐

Stability (will undergo data security and protection if intentionally change records of students, continuance and tracing of learning)	☐	☐	☐	☐	☐
Testability (software prototype undergo several testing before actual implementation)	☐	☐	☐	☐	☐

PART D: QUESTIONS RELIABILITY

This part of the survey determine the overall acceptability and reliability of all questions stored both in Bloom Taxonomy Test Module and in the Item Bank Module.

CRITERIA	1 Strongly Disagree	2 Disagree	3 Neutral	4 Agree	5 Strongly Agree
D1: BLOOM TAXOMY					
Do you agree that the different question types are properly grouped according to Bloom Taxonomy stages?	☐	☐	☐	☐	☐
Do you agree that all the questions presented in each question types are properly classified according Bloom Taxonomy stages?	☐	☐	☐	☐	☐
Do you agree how question difficulty level in each stage of Bloom Taxonomy as properly classified?	☐	☐	☐	☐	☐
D2: ITEM BANK					
Do you agree how the questions are grouped in different question types?	☐	☐	☐	☐	☐
Do you agree how questions difficulty level differ during practice exams and final exams?	☐	☐	☐	☐	☐
Do you agree that the questions asked covered or represented all the topics in a lesson?	☐	☐	☐	☐	☐

Thank you very much for your participation and we look forward to sharing with you the outcome of the research.

Appendix B: Research Questionnaires for Student

Sirte University
Faculty of Science
Department of Computer Science

RESEARCH QUESTIONNAIRES
(for Students only)

Roulette Wheel Selection Algorithms (RWSA) and Reinforcement Learning (RL)
for Personalizing and Improving E-learning System

Confidentiality/Non-Disclosure Assurance

- My research on e-learning development and implementation focused in Libyan setting and is specifically conducted at Sirte University. The overall purpose of the research is to help students excel academically and outperform independently traditional learning using revolutionary technique in experimental way. The results will be presented as insights to the university for further study and adaptation of the new educational platform.
- The data and/or information collected shall be treated with utmost confidence and shall not be shared without prior permission from the respondents.

Research Objectives

- To collect personal data among students and establish respondents' overall information.
- To evaluate students responses with regard to features and functionalities of the e-learning system prototype.
- To correlate the perceptions and experiences of students to the results of the experimental study (academic performance) in using the e-learning prototype.

Directions in Responding to the Questionnaires:

- Please check (√) the box that corresponds to each question. If you want to change your answer, put an X in the previous answer and check a new box that correspond to your new answer.
- To answer Part C, a space is provided, but, you can use additional paper for your comments. Please write your comments clearly and legibly.

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PART A: YOUR PERSONAL DATA

A1. Student Name: (Optional)

A2. Age:

A3. Year Level:

A4. Gender. Male: ☐ Female: ☐

A5. Do you have electronic device readily available to connect to the Internet: Yes: ☐ No: ☐

A6. If you answer Yes, which of the following devices can be used to connect to the Internet?

Laptop: ☐ PC: ☐ Mobile: ☐ Tab: ☐ Others: ☐

A7. Do you have Internet connection in your house? Yes: ☐ No: ☐

A8. If Yes, which internet services?

WiMax: ☐ RiFi: ☐ MyDSL: ☐ Others: ☐

PART B: FEATURES and FUNCTIONALITY PARAMETERS of the E-LEARNING PROTOTYPE

This area will give feedback on how student view the content and instructional design of the e-learning system prototype and evaluate its features and functionalities for student currently enrolled in Design and Analysis of Algorithms. Applying Likert Scale of 1 to 5, kindly evaluate the following questions in each criteria, as honestly as you can.

CRITERIA	1 Strongly Disagree	2 Disagree	3 Neutral	4 Agree	5 Strongly Agree
B1. CONTENT					
Vocabulary and terminology used are appropriate .	☐	☐	☐	☐	☐
Abstract concepts are illustrated with concrete examples.	☐	☐	☐	☐	☐
Course handouts and printing of learning materials are allowed.	☐	☐	☐	☐	☐
Presentation, videos, images, figures, tables and other media for illustrative materials are included.	☐	☐	☐	☐	☐
Reference materials and web guides	☐	☐	☐	☐	☐

are included.					
B2. VISUAL DESIGN					
Fonts (style, color and saturation) are easy to read.	☐	☐	☐	☐	☐
Contrast – differentiate important elements to draw eyes.	☐	☐	☐	☐	☐
Repetition – internal consistency of design templates.	☐	☐	☐	☐	☐
Alignment – design and grid (horizontal/vertical aspects)	☐	☐	☐	☐	☐
Visual impact – neutrality, proximity and influence to mental model.	☐	☐	☐	☐	☐
B3. ACCESSIBILITY					
The course is free from technical problems (hyperlink errors and programming errors).	☐	☐	☐	☐	☐
Course materials are available both online (internet based) and offline (Intranet based).	☐	☐	☐	☐	☐
It can run in different browser and OS platform.	☐	☐	☐	☐	☐
It provides printed materials for personal use (without pedagogical conflict).	☐	☐	☐	☐	☐
Exam and assessment are available online and offline (equal opportunities).	☐	☐	☐	☐	☐
B4. SELF ASSESSMENT					
Learners can start and locate the course, register and access starting page.	☐	☐	☐	☐	☐
The course provides practice exam and feedback mechanism.	☐	☐	☐	☐	☐
It provides grades and other performance matrix analysis.	☐	☐	☐	☐	☐
It encourage self learning and is automatically adjusted to learner's level.	☐	☐	☐	☐	☐
It has final assessment and exam	☐	☐	☐	☐	☐
B5. NAVIGATION					
Learners always know where they are in the course.	☐	☐	☐	☐	☐
The course allows learner to leave whenever they desire to but they can easily return to the closest	☐	☐	☐	☐	☐

logical point in the course.					
Menus and navigational panel are readily available.	☐	☐	☐	☐	☐
It discourages multiple open windows and overloaded pop-up reminders.	☐	☐	☐	☐	☐
It provides direction to provide navigational problem.	☐	☐	☐	☐	☐
B6. LEARNING SUPPORT					
The course offers tools that support learning.	☐	☐	☐	☐	☐
The course includes activities both individual-based and group-based.	☐	☐	☐	☐	☐
It provides additional learning materials.	☐	☐	☐	☐	☐
It provides helps and explanation.	☐	☐	☐	☐	☐
It allows social network media to facilitate collaboration and social learning.	☐	☐	☐	☐	☐
B7. INTERACTIVITY					
The courses use games, simulations and case studies to gain attention and maintain motivation.	☐	☐	☐	☐	☐
It allows “learning by doing” (playing and feeling involved).	☐	☐	☐	☐	☐
Learners can find the activity useful in learning the materials.	☐	☐	☐	☐	☐
It provides simulations and visualization tools to help students understand the materials.	☐	☐	☐	☐	☐
It provides collaborative and interactivity (communications with other learners such as video conferencing, virtual help and etc).	☐	☐	☐	☐	☐

PART C: PERSONAL COMMENT/S

What is the overall impact of the e-learning system for the whole semester for you? Do you think it helps you in someway in improving your learning process? Write your experiences or perceptions in using the e-learning system prototype.

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Thank you very much for your participation and we look forward to sharing with you the outcome of the research.

Appendix C: Sample Question Stems Based on Revised Bloom's Taxonomy

Remember	Who? Where? Which one? What? How? Why? How much? How many? When? What does it mean? What happened after? What is the best one? Can you name all the …? Who spoke to …? Which is true or false?
Understand	What does this mean?, Which are the facts? State in your own words. Is this the same as …? Give an example. Select the best definition. Condense this paragraph. What would happen if …? Explain why . . ., What expectations are there? Read the graph (table). What are they saying? This represents . . . What seems to be …? Is it valid that …? What seems likely? Show in a graph, table. Which statements support …? What restrictions would you add? Outline . . . What could have happened next?, Can you clarify. . .? Can you illustrate . . . ?Does everyone think in the way that … does?
Apply	Predict what would happen if ... Choose the best statements that apply. Judge the effects of … What would result …? Tell what would happen if … Tell how, when, where, why. Tell how much change there would be if … Identify the results of … Write in your own words … How would you explain …? Write a brief outline … What do you think could have happened next? Who do you think…? What was the main idea …? Clarify why … Illustrate the … Does everyone act in the way that … does? Draw a story map. Explain why a character acted in the way that he did. Do you know of another instance where …? Can you group by characteristics such as …? Which factors would you change if …? What questions would you ask of …? From the information given, can you develop a set of instructions about …?
Analyze	What is the function of …? What's fact? Opinion? What assumptions …? What statement is relevant? What motive is there? What conclusions? What does the author believe? What does the author assume?

	State the point of view of … What ideas apply? What ideas justify the conclusion? What's the relationship between? The least essential statements are… What's the main idea? Theme? What literary form is used? What persuasive technique is used? Determine the point of view, bias, values, or intent underlying presented material. Which events could not have happened? If … happened, what might the ending have been? How is … similar to …? What do you see as other possible outcomes? Why did … changes occur? Can you explain what must have happened when …? What were some of the motives behind …? What was the turning point? What are some of the problems of …? Can you distinguish between …?
Evaluate	What fallacies, consistencies, inconsistencies appear? Which is more important, moral, better, logical, valid, appropriate? Find the errors. Is there a better solution to …? Judge the value of … What do you think about …? Can you defend your position about …? Do you think … is a good or bad thing? How would you have handled …? What changes to … would you recommend? Do you believe …? How would you feel if …? How effective are …? What are the consequences of …? What influence will … have on our lives? What are the pros and cons of …? Why is … of value? What are the alternatives? Who will gain and who will lose?
Create	Can you design a … to …? Can you see a possible solution to …? If you had access to all resources, how would you deal with …? Why don't you devise your own way to …? What would happen if? How many ways can you …? Can you create new and unusual uses for …? Can you develop a proposal which would …? How would you test …? Propose an alternative. How else would you …? State a rule.

Appendix D: Digital Transcripts of Students

"Construct knowledge is evident because I understand the concepts by using examples and actual discussion."

"My skills is improved, I was able to read the materials and clarify things during class discussion. The e-learning is new in the university."

"Studying online is boring yet it gives me more time to read and reflect the lesson at my own time.

"Examples gives more idea how to solve the problems. I was able to understand the lesson better since I can read the materials many times."

"My self confidence is boasted because I understand the lesson. I think I will pass the course."

"Self confidence is developed for me though it is the first time using the e-learning system."

"Successfully analyzed and understand different sorting techniques and its performance accordingly. I can construct my own and check it complexity."

"I learned from others. My knowledge is increased as I analyzed example and time complexity."

"Feedback and review mechanism is provided thereby increasing our skills and thinking."

"Can construct knowledge and skills."

"The course give me more understanding and confidence in solving problems since I can go back anytime in reading the course and my skills improved."

"My skills improved in using the system. I don't rely anymore."

"The system gives me new experienced and my skill is improved."

"I helped my classmates to construct knowledge and make his own examples."

"it's fun for the first time and help me more to understand the lessons. I have more confidence in passing the course."

"I am confident that I can pass the course because of the practice exams given by the system."

"Construct knowledge by making my own examples and I am very happy to study."

"I am happy in using the system."

"Skills and critical thinking improved by giving feedback and practice exams."

"The computations of my exam result is not shown, but I am happy because it's a new teaching methods. I am more confident now."

"Develop skills for easy understanding of algorithms."

"The main of objective of the course is for us to learn batter, It improve my learning because I have more time to read at home by accessing in the net and chat with my friends."

"This is the first time and I am very happy and confident. The reinforcement process is more on reading."

"I wanted to have many videos and more on simulations . Simulations is limited."

"Skill acquisition and knowledge discovery can be developed if motivation is more. The system is new for us."

"Construct my own examples that runs in a particular time. Reinforcement process is very long."

"The system will not allow me to go to another exam if I did not passed the previous one. It's fun for the first time and help me more to understand the lessons. I developed my skills."

"Confident that I can pass the course because of the practice exams."

"Initially very hard to follow the learning course eventually I appreciated because of the examples and help from my classmates."

"Skills improved I was able to read the materials and clarify things during the class discussion and do instructions easily."

"I analyzed the examples and gives me more idea how solve the problems. I was able to understand it better and my skill is good."

"Confidence with myself because I understand the topics and can share it my classmates."

"Confidence is what developed. This is my first time."

"My friend and I help each other both online and blended learning."

"The practice exams is confusing but allows you to review more concepts using different questions types."

Appendix E: Semantria Extraction

Detailed | Discovery (one per line)

This mode takes a single document, categorizes it, extracts entities, determines sentiment and creates a summary.

Twitter-like content   English

performance accordingly. I can construct my own and check it complexity."
"I learned from others. My knowledge is increased as I analyzed example and time complexity."
"Feedback and review mechanism is provided thereby increasing our skills and thinking."
"Can construct knowledge and skills."
"The course give me more understanding and confidence in solving problems since I can go back anytime in reading the course and my skills improved."
"My skills improved in using the system. I don't rely anymore."
"The system gives me new experienced and my skill is improved."
"I helped my classmates to construct knowledge and make his own examples."
"it's fun for the first time and help me more to understand the lessons. I have more confidence in passing the course."
"I am confident that I can pass the course because of the practice exams given by the system."
"Construct knowledge by making my own examples and I am very happy to study."

Start Analysis

Current Character Count: 0 / 16384

This document is: **positive (+0.312)**

better easy good improve
very happy motivation
reinforcement friends knowledge
thereby increasing friend rely improved
easily successfully
understanding appreciated confident
experienced happy

Scroll down for full report

Summary

"Construct knowledge is evident because I understand the concepts by using examples and actual discussion."... "Studying online is boring yet it gives me more time to read and reflect the lesson at my own time... "it's fun for the first time and help me more to understand the lessons...

10 entities

Extracted entities	Evidence	Sentiment
"My skills is improved, I was able to read the materials and clarify things during class discussion. The e-learning is new in the university."	**2**	**+0.49**
"Studying online is boring yet it gives me more time to read and reflect the lesson at my own time.;"	**2**	**-0.12**

10 themes

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Extracted themes	Evidence	Sentiment
Self confidence	**7**	**+0.34**
Studying online	**7**	**0.00**
e-learning system	**7**	**+0.37**
analyzed example	**7**	**+1.47**
time complexity	**7**	**+1.75**
practice exams	**7**	**+0.89**
exam result	**7**	**+1.29**
teaching methods	**7**	**+1.40**
critical thinking	**7**	**-0.98**
giving feedback	**7**	**+0.36**